Eine vergleichende Studie zur Optimierung in der Strukturakustik

(A Comparative Study on Optimization in Structural Acoustics)

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Abstract

This dissertation presents an exhaustive comparative study on optimization in structural acoustics. A combination of a commercially available finite element software package and additional user-written programs is used to modify the shape of a structure. This is done iteratively and without manual intervention to achieve significant improvements of the objective function. The optimization process continues automatically until the predefined maximum number of function evaluations is reached.

The design variables are the structure's local geometry modification values at selected surface key-points. The objective of the optimization includes the minimization of the root mean square level of structure borne sound (a general measure of the vibrational sensitivity of a structure). In addition, the structural mass remains constant and the allowable ranges of design variable values are restricted by prescribed upper and lower limits. The optimization procedure is tested on the finite element model of a rectangular plate made of steel.

Twelve different optimization methods are tested against each others. These methods are considered either as approximate or exact. The approximate optimization methods use either an approximated value of objective function, e.g., hybrid design of experiments and hybrid neural networks, or the approximated values of the first and the second derivatives of the objective function, e.g., method of feasible directions, sequential quadratic programming method, Newton method, limited memory Broyden-Fletcher-Goldfarb-Shanno method for bound constrained problems, method of moving asymptotes, mid-range multi-points method and controlled random search method. The exact optimization methods, e.g., genetic algorithms, tabu search and simulated annealing, are derivative-free methods and they use the exact value of objective function. Furthermore, a statistical approach is followed for the comparison of methods. Advantages and disadvantages of each optimization algorithm are reported in details.

The rate of convergence (a measure of optimization speed) and the robustness level of each optimization method are evaluated. Some optimization methods are classified as fast, medium and slow. Method of moving asymptotes and mid-range multi-points method are introduced as the fastest methods.

Finally, it is experienced that the use of effective structural-acoustic analysis methods can drastically reduce the total optimization time. If the powerful optimization methods become equipped with effective (fast and reliable) structural acoustic analysis methods, then they can present more desirable optimization results in a shorter period of computation time. In this case, they can even be considered as a suitable replacement for the complex and the multi-stages hybrid optimization algorithms.

Zusammenfassung

Die vorliegende Dissertation präsentiert eine vergleichende Studie zur Optimierung in der Strukturakustik. Eine Kombination aus einem kommerziellen Finite-Elemente-Software-Paket und der im Rahmen der Arbeit entwickelten zusätzlichen Programme wird verwendet, um die Geometrie einer mechanischen Struktur zu optimieren. Der automatische Optimierungsprozess wird so lange durchgeführt, bis eine vorgegebene maximale Anzahl an Auswertungen der Zielfunktion erreicht wird.

Entwurfsvariablen sind die lokalen Geometrieänderungen an ausgewählten Oberflächenpunkten. Das Ziel der Optimierung umfasst die Minimierung des Effektivwertes der Schallleistung. Der zulässige Bereich der Entwurfsvariablen wird begrenzt. Das Optimierungsverfahren wird an einer rechteckigen Platte aus Stahl erprobt.

Zwölf verschiedene Optimierungsverfahren werden miteinander verglichen. Diese Verfahren sind entweder exakt oder approximativ. Die approximativen Methoden verwenden entweder einen näherungsweisen Wert der Zielfunktion; z. B. Hybrid-Design von Experimenten und hybride neuronale Netze; oder die näherungsweisen Werte der ersten und zweiten Ableitungen der Zielfunktion; z. B. Methode der zulässigen Richtungen, Methode der sequentiellen quadratischen Programmierung, Newton-Methode, BFGS Verfahren, Methode der veränderlichen Asymptoten, Mid-Range-Multi-Punkt-Methode und kontrollierte Zufallsiteration. Die exakten Verfahren sind z. B. der genetische Algorithmus, Tabu Search und Simulated Annealing. Diese sind ableitungsfreie Methoden. Sie verwenden den genauen Wert der Zielfunktion. Zum Vergleich der Optimierungsverfahren wird ein statistischer Ansatz verwendet. Die Vor- und Nachteile der Methoden werden diskutiert.

Die Konvergenzrate (ein Maß für die Optimierungsgeschwindigkeit) und die Robustheit der einzelnen Optimierungsmethoden werden bewertet. Die Methode der veränderlichen Asymptoten und Mid-Range-Multi-Punkt-Methode wurden als effiziente Optimierungsverfahren identifiziert.

Weiterhin wird gezeigt, dass die Verwendung einer effizienten strukturakustischen Analysemethode zu einer drastischen Verringerung der für die Optimierung benötigten Rechenzeit führt.

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DEDICATED TO THE SPIRIT OF MY BELOVED MOTHER
MANIJHEH REZAIEE DEHSHIBI,
(1957-2007)

Contents

List of Symbols and Acronyms

Latin Symbols

A	surface area of an element face [m^2]
c	speed of sound [m/s]
c_a	speed of sound in air [m/s]
$c_i(\boldsymbol{\vartheta})$	constraint
$c(\boldsymbol{\vartheta})$	vector of constraints
$c_{eq}(\boldsymbol{\vartheta})$	vector of equality constraints
$c_{ineq}(\boldsymbol{\vartheta})$	vector of inequality constraints
d_k	search line in $k^{th.}$ iteration
E	Young's modulus, elastic modulus [N/m^2]
f	frequency [Hz]
F	force, excitation force [N]
$\mathcal{F}$	objective function
f_1	fundamental frequency [Hz]
g	matrix of the first derivatives of $\mathcal{F}$
h	admittance [m/(N s)]
h_t	transmission admittance [m/(N s)]
H	Hessian matrix
i	index number for design variables ($i = 1, \cdots, n.$)
k	number of iterations
L	level [dB]
L_P	sound power level [dB] (reference value $P_0 = 10^{-12}$ W)
$L_{Sh_t^2}$	level of structure borne sound (LS) [dB] (reference value $S_0 h_{t0}^2 = 2.5 \cdot 10^{-15}$ m^4/(N^{2}s^2))
$\overline{L_{Sh_t^2}}$	mean level of structure borne sound (MLS) [dB]
n	number of design variables
N	number of start points located in each segment of domain
N_G	number of generations (Genetic Algorithm)
N_p	population size (Genetic Algorithm)
n_R	total number of uniform random start points
N_s	total number of equal segments between 0 and 1
p	sound pressure [kg/m.s^2]
P	radiated sound power [W]
S	surface area [m^2]
t	plate thickness [m]
$\boldsymbol{\upsilon}$	velocity vector [m/s]
υ	velocity [m/s]
υ^*	conjugate complex of υ
$\upsilon_\perp$	normal surface velocity [m/s]
υ_{rms}	rms velocity [m/s]
$\upsilon_{rms\imath}$	rms velocity of some point $\imath$ [m/s]
$\boldsymbol{\vartheta}$	vector of design variables
ϑ_i	design variable, design parameter

ϑ_{ini}	initial uniform random points between 0 and 1
ϑ_{max}	upper bound constraint on design variables
ϑ_{min}	lower bound constraint on design variables
$x,\ y,\ z$	global coordinates
Z_a	specific impedance of air

Greek Symbols

α	moving limit factor
Δ	difference between two values
ν	Poisson's ratio
ρ	material density [kg/m^3]
ρ_a	density of air [kg/m^3]
σ	radiation efficiency
ψ	convergence rate
ω	circular frequency [Hz]

Subscripts, Superscripts, and Other Symbols

$\langle\rangle_{min}$	lower limit (predefined prior to optimization)
$\langle\rangle_{max}$	upper limit (predefined prior to optimization)
$\overline{\langle\rangle}$	mean value, average
$\langle\rangle_{\perp}$	normal to surface
$\langle\rangle_{rms}$	root mean square value
$\langle\rangle_{n}$	unit normal vector
$\mathbb{N}$	set of integer numbers
$\mathbb{R}$	set of rational numbers
$\Re^n$	n-dimensional search space

Acronyms and Abbreviations

BEM	**B**oundary **E**lement **M**ethod
BFGS	**B**royden-**F**lecher-**G**oldfarb-**S**hanno algorithm
CRSM	**C**ontrolled **R**andom **S**earch **M**ethod
CPU	**C**entral **P**rocessing **U**nit
DOE	**D**esign **O**f **E**xperiments
DOF	**D**egree **O**f **F**reedom
FE	**F**inite **E**lement
FEA	**F**inite **E**lement **A**nalysis
FEM	**F**inite **E**lement **M**ethod
FDM	**F**inite **D**ifference **M**ethod
fnvs	Number of **fun**ction e**v**aluation**s**
FRF	**F**requency **R**esponse **F**unction
FS	**F**inite **S**trip
GA	**G**enetic **A**lgorithm

HDOE	**H**ybrid **D**esign **O**f **E**xperiments
HNN	**H**ybrid **N**eural **N**etworks
IEM	**I**nfinite **E**lement **M**ethod
IMSL	**I**nternational **M**athematical and **S**tatistical **L**ibrary
ISO	**I**nternational **O**rganization for **S**tandardization
L-BFGS-B	**L**imited (Memory)-**BFGS** for **B**ound Constrained Optimization
LS	**L**evel of **S**tructure borne sound
MFD	**M**ethod of **F**easible **D**irections
MLS	**M**ean **L**evel of **S**tructure borne sound
MMA	**M**ethod of **M**oving **A**symptotes
MMP	**M**id-range **M**ulti-**P**oints method
MPI	**M**essage **P**assing **I**nterface
MRI	**M**agnetic **R**esponde **I**maging
NAG	**N**umerical **A**lgorithms **G**roup
NM	**N**ewton **M**ethod
NN	**N**eural **N**etworks
OPL	**O**verall **P**erformance **L**evel
rms	**r**oot **m**ean **s**quare
RMSL	**R**oot **M**ean **S**quare **L**evel
SA	**S**imulated **A**nnealing
SPL	**S**ound **P**ressure **L**evel
SQP	**S**equential **Q**uadratic **P**rogramming
SR	**S**uccess **R**ate
TL	**T**ransmission **L**oss
TS	**T**abu **S**earch

Chapter 1

Introduction

This dissertation deals with numerical methods for structural acoustic optimization of three-dimensional structures. The following section provides some information on the background of and the motivation for the present study. The literature survey in Sec. 1.2 reviews and summarizes many books and dissertations as well as numerous conference papers and scientific journal articles. Sec. 1.3 discusses about the history of hybrid robust shape optimization in structural acoustics. Section 1.4 describes the scope and objectives of this research. Finally, the outline in Sec. 1.5 explains how the remainder of this work is organized.

1.1 Background and Motivation

Noise pollution, annoyance, and hearing impairment have been a problem since the beginning of industrialization in the 18th and 19th century. More and faster cars, trains, and airplanes have increased this problem within the last 30 or 40 years. Also, in almost every household, workshop, or factory, there are noisy appliances and loud machines such as blow-dryers, food processors, vacuum cleaners, drills, lathes, punches, presses, conveyor belts, etc.

A lot has been done already to protect workers, population, and environment: new environmental laws and regulations; noise barriers alongside roads, highways, railroad tracks, and airports; new developments in car tires, train wheels, engines, and aerodynamics; quieter airplane engines; quieter industrial machines, etc. But there remain much to be done, and the legislative pressure on the manufacturers to make their products quieter increases on an almost annual basis.

On the other hand, there is a demand that machines and their components become lighter (lightweight design) in order to save fuel or decrease energy consumption as well as faster in order to produce more parts per unit time or to shorten travel times. Unfortunately, these tendencies are somewhat contradictory to the demand of quiet products, since light structures tend to be noisier than heavy ones, and fast machines incline to be louder than slow ones.

It is desirable to include noise-reducing measures into the design process of parts and machines (primary noise reduction at the source) rather than trying to reduce the radiated noise of conventionally designed structures and machines afterwards by damping treatments and encapsulation (secondary noise reduction of radiated sound) [Kollmann 00]. One way to achieve this is to conduct numerical simulations on virtual computer models during the design phase of a product [Koopmann 97, Lyon 00]. Problem zones can be detected at an early stage, and it is possible to modify the design such that the product sounds good (e.g., a sports car) or is substantially quieter than before (e.g., trains, airplanes). This approach is called "virtual acoustic prototyping".

Primary noise reduction can be further subdivided into active as opposed to passive noise control. Active noise control uses sensors, controllers, and loudspeakers, which generate a secondary sound field that (partially) cancels the original sound field within a defined volume [Nelson 92]. Another approach is active structural acoustic control in which structurally radiated sound is directly controlled by active structural inputs [Fuller 96]. Passive noise control describes procedures that influence the acoustical properties of structures by modifying their shape or thickness, adding stiffeners (ribs, beads, etc.) or masses, or applying additional layers of damping material to the surface. The latter approach motivates the present work. It describes methods to optimize structures numerically with respect to various acoustical and structural properties such as root mean square level of structure borne sound (a measure of the vibrational sensitivity of a structure), structural mass, natural frequencies, etc. These techniques can be applied during the design phase of a machine or machine component, since they use a finite element (FE) model of the structure. The shape of the structure, i.e., its geometry, is modified automatically such that the desired goal is achieved without violating given constraints. The procedures can also serve the purpose of lightweight design because they are able to reduce the level of structure borne sound without applying additional mass due to the optional definition of suitable constraints.

1.2 Literature Review

The present dissertation deals with a range of different disciplines including acoustics (particularly structural acoustics), optimization methods, the finite element method (FEM), geometric design, etc. Numerous textbooks, dissertations, and scientific journal papers are available for each of these topics. Thus, although this literature review is relatively detailed and exhaustive, it can present just an overview of the available background literature in some of the fields.

1.2.1 Optimization in Structural Acoustics

There are only a limited number of textbooks that deal with numerical optimization in acoustics or structural acoustics. Koopmann and Fahnline [Koopmann 97] were the first to publish a textbook solely on designing quiet structures by means of a sound power minimization approach. A chapter in the textbook on machine acoustics by Kollmann [Kollmann 00] focuses on structural acoustic optimization. The paper by Olhoff [Olhoff 70] on the optimal design of vibrating circular plates is one of the first works in the field of numerical optimization in acoustics. He maximized the fundamental frequency of rotationally symmetric plates by optimizing the shape of the plates for a given volume, diameter, and Poisson's ratio.

Lyon, Mark, and Pyle Jr. [Lyon 73] conducted theoretical and numerical studies to reduce the noise radiated from helicopter rotor tips. The shape of the rotor blades was optimized in order to minimize the radiated sound power subject to prescribed upper and lower bounds on the allowable longitudinal section area using a steepest descent method. A sound power reduction of approximately 10 dB was achieved in some frequency bands up to 5500 Hz.

A paper by Franco et al. [Franco 07] presented the optimization of various innovative sandwich configurations for minimization of their structural-acoustic response. The results demonstrated how the proper selection of selected key parameters can achieve effective reduction of the radiated sound power and how the identified optimal configurations can achieve noise reduction over different frequency ranges and for various source configurations.

Denli and Sun [Denli 07] presented an optimization study of sandwich structures with cellular cores for minimum noise radiation in a wide frequency band, subject to the constraints on the fundamental frequency and weight. Sensitivity functions of the radiated acoustic power were used to improve the computational time and accuracy. Numerical examples indicated that significant reduction of narrow-band and broadband sound radiation can be achieved.

Lalor [Lalor 80] used static deflection techniques to simplify the FE calculations. The overall noise level was reduced by up to 5 dB subject to weight, space, and strength constraints. However, it is not clear if numerical optimization techniques were used in this process. Rather, it appears as if FE analysis just helped to identify regions of the engine block that should be modified in order to achieve reduced noise levels. The actual modifications seem to be applied manually.

In another paper by Wilcox and Lalor [Wilcox 87], a simple univariate algorithm with four design variables and a fixed step length line search reduced the noise of an engine by changing the shape of the crankcase. The obtained noise reduction of 2.1 dB was verified by experiments in which a noise reduction of 2.0 dB in a frequency band from 500 to 3200 Hz was measured.

Yildiz and Stevens [Yildiz 85] optimized the thickness of unconstrained viscoelastic damping layer treatments for plates. Their objective was the maximization of the system loss factor by means of varying the mechanical properties of the plate and the damping layer as well as the layer/plate thickness ratio. An increase of the system loss factor by more than 100% is reported.

A method for sensitivity analysis and optimization of nodal point locations in connection with vibration reduction was developed by Pritchard, Adelman, and Haftka [Pritchard 87]. The sizes of added lumped masses on helicopter rotor blades were used as design variables to move nodal positions to a preselected location. The objective function that was to be minimized was the sum of the added masses. A potential application of nodal point placement is the reduction of overall vibration response by generalized force minimization.

Lamancusa [Lamancusa 88] addressed the geometric optimization of internal combustion engine induction systems. He used the IMSL optimization subroutine to perform global optimization but did not provide further information as to how this algorithm works. He just states that this routine seems to function well and achieves convergence. The aim was to control the low frequency inlet noise of a 4-cylinder automobile engine by optimizing the pipe lengths of an intake manifold system using up to three design parameters. The average exit sound pressure in the frequency range 50-250 Hz was reduced by up to 20 dB, primarily by shifting the major response peaks out of the frequency range under consideration. The analytically predicted noise reductions were verified experimentally.

Optimum vibrating shapes of beams and circular plates were investigated by Thambiratnam and Thevendran [Thambiratnam 88]. They optimized the thickness to maximize the fundamental frequency, keeping the volume of the structure constant, or to minimize the volume and shape of the structure for a given minimum allowable fundamental frequency. Various boundary conditions were employed, and the Complex algorithm [Box 1965] was used, incorporating the constraints into the objective function as a penalty function. The optimization results varied with the boundary conditions. The authors reported a fundamental frequency increase of up to 350% and a volume decrease of up to 75%.

In a series of papers by various combinations of the authors Belegundu, Constans, Cunefare, Lamancusa, Koopmann, Naghshineh, and Salagame, the weak radiator concept was introduced and applied to several problems. A weak radiator is a mode that radiates sound very inefficiently due to a low net volume velocity. This is achieved by pressure cancelations at the surface of the plate (acoustic short circuit), leaving very little energy left to be radiated by the plate's edges. The sound power output from a structure was minimized by changing a mode shape or several mode shapes of the structure into a weak radiator using material tailoring [Naghshineh 92], placing strategically sized masses at specific locations [Constans 98], optimizing the thickness distribution [Lamancusa 91, Lamancusa 93, Belegundu 94], or using active control forces [Naghshineh 94]. Cunefare [Cunefare 91a] developed a technique for deriving the optimal surface velocity distribution of a finite baffled beam that minimizes the radiation efficiency of the beam. Lamancusa and Koopmann [Lamancusa 91] employed four different strategies to minimize the radiated sound power from a rectangular plate, namely, minimization of radiated sound power at a single frequency, minimization of radiated sound power over a frequency band, minimization of the radiation efficiency over a number of modes, and forcing the plate to vibrate with a mode shape that is a weak radiator. They used a method of feasible directions to optimize the thickness distribution of the plate and obtained a radiated sound power reduction of 9.1 dB in the first case (800 Hz), an improvement of 2.2 dB in the second case (0-800 Hz), and a decrease of 10.2 dB in the third case (first six modes). Results for the fourth case were not provided. Naghshineh, Koopmann, and Belegundu [Naghshineh 92] employed material tailoring to achieve a minimum radiation condition. In the first step, a surface velocity distribution with minimum radiation condition, a so-called weak radiator velocity profile, must be obtained by some FE scheme. In a second step, a distribution of Young's modulus and a density distribution is generated by structural FE modeling and linear programming techniques such that the structure exhibits the weak radiator profile as one of its mode shapes. A finite baffled beam was chosen to illustrate this approach. Lamancusa [Lamancusa 93] found optimal thickness distributions of rectangular, at plates with clamped edges that minimize the acoustic response to point forces at a single frequency or over a wide frequency bandwidth. He states that appropriate objective functions and constraints are critical to optimization success and lists some possible candidates: total weight, placement of structural natural frequencies, mode shape, mean square velocity, radiation efficiency, total radiated sound power, and matching of a predetermined weak radiator mode shape. An optimization program based on the method of feasible directions is used to optimize the thickness of rectangular plates for various mentioned objective functions subject to appropriate constraints. Belegundu, Salagame, and Koopmann [Belegundu 94] minimized the radiated acoustic power of a baffled plate by optimization of the thickness distribution and produced weak radiator mode shapes as well. They calculated the design sensitivity coefficients for gradient-based optimization analytically and applied their approach to the optimization of an engine timing chain cover plate. The total power radiated from the first three modes was reduced by 12 dB while, interestingly, the weight is decreased as well by 32%. A modal tailoring approach was used by Constans, Koopmann, and Belegundu [Constans 98] to minimize the sound power radiated from a vibrating shell structure. They employed a simulated annealing (SA) algorithm to place two small masses (35.8 g) at optimal FE node positions on a half-cylindrical aluminum shell in such a way that the radiated sound power (considering the first five modes) was minimized. The four design variables were the axial and circumferential coordinates for both masses. As a result of the optimization, the structure was converted to a weak radiator, leading to a sound power reduction of 9.5 dB at the first three modes. These findings were confirmed by experimental measurements.

A paper presented by Sivakumar, Sung, and Nefske [Sivakumar 91] describes the noise reduction of engine component covers. No numerical optimization was performed, but rather the forced vibration response was predicted by means of FEM, and manual design variations employed to reduce the radiated sound power. The predicted noise reduction of 2.7 dB through the addition of stiffening ribs was surpassed by a 4.5 dB reduction measured in experiments. When the material of an engine front cover was changed from steel to laminated steel, a decrease of 6.2 dB (predicted) and 8 dB (measured) was achieved.

Cunefare and Koopmann [Cunefare 92] developed an acoustic design sensitivity analysis technique by means of a boundary element method (BEM) formulation of the Helmholtz integral equation and partial differentiation of a quadratic power expression with respect to known surface velocities. This procedure leads to a sensitivity distribution, which quantifies the incremental change in radiated sound power from three-dimensional structures due to incremental changes in the surface normal velocity. Regions with high sensitivity would be likely candidates for the placement of active sources or for design modifications. The method was successfully applied to a rectangular box and a right circular cylinder.

In another series of papers, Hinton, Q̈zakça, Rao, and Sienz focused on the free vibration analysis and shape optimization of axisymmetric plates and shells, variable thickness plates, prismatic folded plates, and curved shells. Hinton, Q̈zakça, and Sienz [Hinton 93] optimized simply supported and clamped plates as well as conical, spherical, and branched shells with respect to certain vibration characteristics. They used cubic splines to define the overall geometry and thickness variation. A semi-analytical sensitivity analysis was combined with a sequential quadratic programming (SQP) optimization algorithm. In the first part of their article, Q̈zakça and Hinton [Q̈zakça 94a] derived new FE element formulations, forming a family of variable thickness, curved C(0) Mindlin-Reissner axisymmetric elements that include shear deformation and rotatory inertia effects. Accuracy, convergence, and efficiency were tested by free vibration analysis and comparison with other numerical and analytical methods. In the second part [Q̈zakça 94b], these new elements were used for shape optimization of axisymmetric plates and shells. Shape and thickness of conical shells, circular plates, branched shells, and bells were optimized either to maximize certain natural frequencies or to minimize the material volume. Cubic splines were used to define shape and thickness. A combination of semi-analytical sensitivity analysis and mathematical programming (SQP from the NAG library) served as optimization algorithm. In the following year, Hinton, Q̈zakça, and Rao again published a two parts paper. The first part [Hinton 95a] describes the free vibration analysis of variable thickness plates, prismatic folded plates, and curved shells carried out by using curved, variable thickness finite strips based on Mindlin-Reissner shell theory. The finite strip (FS) method combines the use of Fourier expansions and one-dimensional finite elements. Accuracy and effectiveness were illustrated on square plates, variable thickness plates in various shapes, cylinders with interior partitions, and a two-cell right box-girder bridge. In the companion paper [Hinton 95b] the FS method was applied to shape optimization of square plates, a cylindrical shell, and a box-girder bridge. A computational tool combines FS analysis, cubic spline geometry definition, semi-analytical sensitivity analysis, and mathematical programming. Shape and thickness were the design variables, objectives were the maximization of the fundamental frequency subject to a volume constraint or the minimization of volume (or weight) subject to frequency constraints.

Inoue, Townsend, and Coy [Inoue 93] optimized the design of a simple model gearbox to minimize the overall vibration energy by varying the finite element thickness subject to lower and upper bounds on the thickness and to constant weight. A modal analysis is performed to derive the sensitivities after which a gradient projection method and a unidimensional search procedure is used to calculate the optimal design. The vibration energy is decreased by about 81% in the frequency band from 500 to 1500 Hz by optimizing just the top plate.

In his Ph.D. dissertation, Broschart [Broschart 94] calculated sound pressure, sound intensity, and sound power of vibrating structures based on BEM and compared the results with measurements performed on rectangular plates and boxes. He reduced the computation time by up to 99% with multigrid methods, applied additional actively controlled forces to reduce the surface velocity level by up to 7 dB, and employed structural optimization to reduce the vibration level, increase the fundamental frequency, or reduce the mass subject to various constraints. Design parameters were the plate thickness and the height and width of additionally applied ribs.

Hambric [Hambric 95] presented various approximation techniques for broadband acoustic radiated noise design optimization. Low-order series approximations replace full numerical systems to save computation time, thus making the models suitable for global search methods such as SA, which usually require a large number of function evaluations. The methods were tested for effectiveness, efficiency, and generality on three test cases in which shell thickness, shell loss factors, and rib stiffener locations served as design variables to minimize weight and manufacturing costs while lowering broadband radiated noise levels below a specified limit. The three test cases were the single octave band, two design variable study and the multiple octave band, four design variable study of a simply supported cylindrical shell with end caps as well as the multiple aspect, multiple octave band, six design variable study of a rib-stiffened cylindrical shell with end caps. In a sequel paper [Hambric 96], the influence of sensitivities on the convergence characteristics was investigated for one of the above mentioned three test cases by varying the design variable step sizes and the frequency resolution.

Keane [Keane 95] investigated passive vibration control via unusual geometries. A genetic algorithm (GA) optimized the position of 36 joints of a network consisting of 40 coupled beams such that the frequency averaged vibrational energy level at one end of the structure was minimized. The frequency range of interest was 150-250 Hz. The results depended on the strictness of the constraints to the design variables: When the joint positions were allowed to vary by up to ±5%, a reduction of 23 dB was achieved, while the vibrational energy was decreased even by 60 dB for a ±25% limit. In a second paper [Keane 96], Keane and Bright describe experiments, which were conducted to verify the above optimization results. Two aluminum alloy structures (scaled down from 10 m to 2.6 m length) representing the original and the optimized structure were built and tested. The detailed behavior showed some deviations from the theoretical design, but good overall agreement between simulation and experiments was observed.

McMillan and Keane [McMillan 96] manually applied five concentrated masses to a thin rectangular plate in order to shift resonances from a frequency band, thus reducing the eigenvalues within certain bounds. Three different analytical approaches were developed for calculating the eigenfunctions, eigenvalues, and frequency response of the mass loaded plates. The results were obtained relatively easily and compared well with those obtained by using FEM. In a subsequent paper by the same authors [McMillan 97], these methods are utilized to place 50 small point masses (totaling 10% of the plate mass) at optimal positions in such a way that a thin rectangular plate has no (or reduced) resonance peaks in its vibration transmission characteristics in a given frequency band. For the optimization, a sequential positioning method was compared with a GA. The former method achieved the greatest suppression of vibration, but the latter performed almost as well.

In vibration optimization problems, eigenfrequencies are usually maximized in the optimization since resonance phenomena in a mechanical structure must be avoided, and maximizing eigenfrequencies can provide a high probability of dynamic stability. However, vibrating mechanical structures can provide additional useful dynamic functions or performance if desired eigenfrequencies and eigenmode shapes in the structures can be implemented. Maeda et al. [Maeda 06] proposed a new topology optimization method for designing vibrating structures that targets desired eigenfrequencies and eigenmode shapes. Several numerical examples were presented to confirm that the method presented there can provide optimized vibrating structures applicable to the design of mechanical resonators and actuators.

A group of researchers led by Marburg published quite a number of articles on acoustic optimization during the period 1997-2003 [Marburg 97a, Marburg 97b, Marburg 00, Marburg 01, Marburg 02c, Marburg 02g, Marburg 02e, Marburg 02d, Marburg 02b, Marburg 02f, Marburg 02a, Fritze 03]. Marburg et al. [Marburg 97a] introduced the concept of acoustic influence coefficients for the optimization of a vehicle roof whose geometry was described by 6 parameters. Optimal shell curvatures, which decrease the sound pressure at the driver's ear, are calculated by a coupled FEM/BEM procedure with one-way structure-fluid interaction, i.e., the structure excites the fluid but not vice versa. Various combinations of objective functions and constraints yielded sound pressure reductions between 3.2 dB for tight constraints and 53 dB for an optimization run without constraints on the design variables. The same approach was used by Marburg et al. [Marburg 97b] in a case study in order to investigate the effects of stiffening a vehicle roof model by additional beams and ribs. An optimization of the geometry based parametric roof model with the objective to minimize the sound pressure at a specified point inside the car resulted in a decrease of 8 dB mainly due to a reduction of the number of natural frequencies in the frequency range of interest. Marburg and Hardtke [Marburg 00] introduced a weighting function that helps the optimizer to focus on the reduction of the high level peaks rather than on the low-level parts of the objective function. Further, they used acoustic influence coefficients and a semi-analytical method for the sensitivity analysis. In another paper, Marburg and Hardtke [Marburg 01] describe the shape optimization of a vehicle hat-shelf. The curvature of the hat-shelf was optimized to maximize the fundamental frequency and, ideally, to shift it out of the frequency range of interest. A multigrid strategy using four different FE discretizations was applied: The coarsest mesh provided initial parameter sets, which were preoptimized with either a refined linear element mesh or a refined quadratic element mesh. An even more refined mesh with a reduced number of parameter sets was then used for the actual optimization. The fundamental frequency was increased from 32 to 101 Hz, thus, out of the frequency range of interest 0-100 Hz. The corresponding sound pressure level was reduced by up to 13.9 dB. In a two-part article, a general concept for the design modification of shell meshes used for acoustic optimization was described. The first part by Marburg [Marburg 02c] focused on the formulation of the concept. A discussion of the advantages and disadvantages of geometry based models led to a division of the domain under investigation into a modification domain and its complement and to the introduction of global modification functions (defined everywhere in the modification domain) and local modification functions (defined only in local modification subdomains). In the second part by Marburg and Hardtke [Marburg 02g], they applied the methods developed in the first part to the curvature optimization of a vehicle floor panel. One global and four local modification functions were defined, totaling 33 design variables. The optimization algorithm was a combination of a random iteration and a gradient-based method. The sound pressure level at the driver's ear was decreased by 2 dB. Marburg et al. [Marburg 02e] experimentally verified results of structural acoustic design optimization. The structure under investigation was a steel box. An experimental modal analysis was performed, and the sound pressure level was measured at three positions inside the box. Both an original and a numerically optimized design of the box were built and tested, and the agreement between simulation and experiment was found to be satisfactory. Another two-part publication describes the efficient optimization of a noise transfer function by modification of a shell structure geometry. The first part by Marburg [Marburg 02b] reviews the theory and concepts of structural and acoustic analysis, structure-fluid coupling, objective function, and sensitivity analysis introduced in earlier papers. A concrete description of the optimization technique used is missing. In the second part by Marburg and Hardtke [Marburg 02f], the concepts described in the first part were applied to the optimization of a vehicle dashboard. The sound pressure at the driver position was to be minimized by optimizing the curvature of the dashboard using various objective functions. Improvements of up to 3.8 dB are reported. Marburg [Marburg 02a] wrote an exhaustive 80-page review article on structural acoustic optimization for passive noise control, which lists 344 references. First, he presented an overview of structural acoustic simulation techniques, various optimization strategies, and problems in structural acoustic optimization. Then, he elaborated on the suitable choice of objective functions and design variables before he provided a survey of optimization results. He concluded his paper with a description of open problems. Fritze, Marburg, and Hardtke [Fritze 03] reduced the frequency averaged radiated sound power in the range 0-250 Hz of plates and shells by local modification of geometry using a gradient-based method. Curvature modifications change the local stiffness without increasing the mass. Parameter studies provided appropriate initial parameters to enhance the efficiency. The position, orientation, and depth of a bead was varied, resulting in six design variables. Sound power reductions of up to 4 dB were achieved.

Pedersen [Pedersen 05] uses a topology optimization approach to sketch over the square and rectangular plates so that a natural frequency is shifted or maximized or that the distance between natural frequencies is maximized.

A review article on analysis and optimization in structural acoustics by Christensen, Sorokin, and Olhoff [Christensen 98b] lists 39 references and focuses on existing numerical methods for solving problems of structural acoustic coupling with an emphasis on analysis, design sensitivity, and optimization. In a companion paper by the same authors [Christensen 98c], some optimization results with respect to the directivity of sound emission were presented for both a flat and conical circular shell. The structures were submerged in water (heavy fluid) in order to study the effects of structural acoustic coupling, which usually can be neglected for light fluids such as air. The radial positions and the mass of 29 circular dead ring masses added to the plate or shell served as design variables subject to appropriate constraints. A method of sequential linear programming was used for the optimization, a simple finite difference approach provided the sensitivities, and a harmonically varying point force of 10 N at 1850 Hz excited the center of the plate. The objective was to achieve a uniformly distributed emission of sound pressure in all directions. Finally, the sensitivity of the obtained optimal design with respect to other, preassigned design parameters that had not been used as actual design variables (damping coefficient, excitation frequency, value of largest mass) was investigated. In a third paper, Christensen and Olhoff [Christensen 98a] performed a directivity optimization of a loudspeaker diaphragm by coupled FEM/BEM calculations. The objective was to uniformize the loudspeaker's directivity properties by optimizing the masses and radial positions of 32 concentric dead ring masses attached to the diaphragm (similar to [Christensen 98c]) or the shape of the diaphragm's mid-surface by using B-splines (up to 10 design variables).

In his Ph.D. dissertation, Hibinger [Hibinger 98] described the optimization of various three-dimensional model structures with respect to vibrational levels, mass, or natural frequencies. He used a revised version of the simplex method of linear programming (first published by Dantzig [Dantzig 63] and completely unrelated to Nelder and Mead's simplex algorithm [Nelder 65] to optimize the thickness of shell elements or the height of additionally applied ribs. He also defined appropriate constraints such as maximum allowable mass, maximum allowable vibration level, minimum and maximum plate thickness or rib height, and maximum allowable thickness or height difference for adjacent elements (continuity condition). Hibinger performed experimental measurements for some of the structures, thus verifying the numerical simulation and optimization results. The vibration level was reduced by up to 11.6 dB, the mass was decreased by up to 35%, and the fundamental frequency was increased by up to 52%.

Lumsdaine and Scott [Lumsdaine 98] dealt with shape optimization of unconstrained viscoelastic layers. According to the authors they were the first to use continuum finite elements for optimization. They reduced the peak displacement of simple, symmetric beam and plate structures by up to 98% in the frequency range from 100 to 1300 Hz (and simultaneously improved the system loss factor by up to 5270%), using an SQP algorithm and the commercial FE program ABAQUS.

Vibrational optimization of a mass-loaded stepped plate was performed by Moshrefi-Torbati, Simonis de Cloke, and Keane [Moshrefi-Torbati 98]. They minimized the integral of the frequency response (i.e., deflection in m per unit force in N) of simply supported stepped plates in the frequency range from 55 to 65 Hz by optimally placing one, two, five, ten, or twenty point masses with a total mass of 5 kg, which was about 10% of the plate's weight. A GA yielded frequency response improvements by up to a factor of 35.

Ratle and Berry [Ratle 98] also used a GA for the vibro-acoustic optimization of a point-loaded and an acoustically excited plate, both carrying point masses. The objective function was either the mean square velocity of the plate or the far field sound pressure level in a prescribed direction, both in the frequency band 200-250 Hz. The goal was to determine the optimal positions of five additional point masses (each one representing 20% of the plate mass). Due to the discretization of the plate, there would have been $64 \times 64 = 4096$ possible positions for placing a single point mass. For the five masses problem, however, about 9.6×10^{15} possible positions exist, making an exhaustive search impossible. Thus, a GA with a large population size (100) and a large number of generations (200) was used. The intuitive solution (i.e., placing all masses on the excitation point) did not yield the optimal placement (56 dB reduction of the mean square velocity level, 28 dB SPL reduction for point force excitation, and even an SPL increase of 4 dB for plane wave excitation), since there were still two peaks in the frequency range of interest. The true optimal placement shifted all natural frequencies out of the frequency range of interest, resulting in a reduction of the mean square velocity level by 70 dB, an SPL reduction of 58 dB for point force excitation, and an SPL decrease by 4 dB for plane wave excitation. The authors also investigated the influence of the correct choice of objective function. When they used the vibratory criterion for the noise reduction, they obtained only a 38 dB SPL reduction as opposed to a 58 dB SPL reduction for the noise radiation criterion. Vice versa, employing the acoustic criterion for the vibration reduction yielded only 56 dB as opposed to 70 dB using the vibration criterion.

Noise radiation of principle gearbox housings with stiffening ribs was investigated by Wender [Wender 98]. Parameter studies conducted on twelve different rib configurations (parallel to the edges, diagonal, star-shaped) of various heights showed that the radiated sound power depends on the arrangement and the height of the ribs. An attenuation of up to 11.5 dB was achieved, but the mass increased by up to 100%.

Tinnsten et al. published a series of papers as well. The wall thicknesses at the FE nodes on the top of a rectangular box were optimized subject to a mass constraint by Tinnsten, Esping, and Jonsson [Tinnsten 99] using a method of moving asymptotes. Four different cases were considered with the sound intensity level at a prescribed position above the box being the objective function in all four cases. The sound intensity level was reduced by up to 56 dB. Tinnsten [Tinnsten 00] compared numerical optimization results with experimental measurements. He optimized the shell thickness of the aluminum top plate of a closed steel cylinder such that the sound intensity level at specified points outside the cylinder was minimized subject to weight and thickness constraints. In case of a free top edge, the sound intensity level was reduced by 4.0 dB in the simulation and by 2.3 dB in the measurements, whereas in case of a clamped top edge it decreased by 14.7 dB in the computation and by 19.5 dB in the experiments. Carlsson and Tinnsten [Carlsson 02] developed a material model for softwood for violin top plates and employed SA to adapt the natural frequencies of a violin top plate made of artificial wood to that of a real one. The thickness distribution of the top plate was optimized using a total of 68 design variables to minimize the weighted sum of the differences between the natural frequencies of the original and the modified top plate, considering the first three eigenmodes. The new thickness values were constrained to $\pm 10\%$ of the original values. The optimal design yielded a maximal natural frequency deviation of 0.048%. In the paper by Tinnsten and Carlsson [Tinnsten 02a], the methods and results presented in the previous paper [Carlsson 02] are described in more detail. Additionally, the arch height of the violin top plate served as an alternative design variable instead of the thickness distribution. This new choice of design parameters led to a slightly inferior optimization result than the old one. Tinnsten, Carlsson, and Jonsson [Tinnsten 02b] presented a numerical and experimental comparison of stochastic optimization results. The same structure as in [Tinnsten 00], i.e., a closed steel cylinder with an aluminum top plate, with the same discretization and the same objective function and constraints, was investigated. The SA optimization algorithm reduced the sound intensity level by 18.7 dB, whereas a reduction of 24.1 dB was measured in the experiment. The numerical optimization results using SA were also compared with the ones obtained from a gradient-based method in [Tinnsten 00]. The SA algorithm reached an optimum where the intensity level was 4 dB lower and the weight of the top plate was 14% lower than that achieved with the gradient-based method.

An engineering toolbox for structural acoustic design was developed and presented in Kessels' Ph.D. dissertation [Kessels 01]. He applied the toolbox to reduce the sound power radiated from MRI scanners and obtained an attenuation of up to 13 dB by optimizing glue modulus and carrier layer thickness.

Kaneda et al. [Kaneda 02] presented an optimization approach for reducing sound power radiated from a vibrating plate by its curvature design. They employed an optimization procedure based on a genetic algorithm (GA), a shape representation technique using B-splines, vibration analysis (FEM), and acoustic radiation analysis (Rayleigh integral formulation).

The curvature of a simply supported square aluminum plate was optimized by varying the positions of six control points in such a way that the radiated sound power is minimized in the frequency band from 10 to 1200 Hz (10 Hz step length). An attenuation of 22 dB was achieved mainly due to shifting the fundamental frequency towards higher values, thus enlarging the quasi-static frequency range. The paper concludes with an interesting investigation, namely, that of the sensitivity and robustness of the optimal design when exposed to small perturbations of the design parameters, which may occur in real life due to unavoidable scatter of properties and boundary conditions caused by manufacturing and assembly tolerances or by thermal expansion and contraction of real systems. Hence, in certain situations it may be more important to focus on the robustness of improved solutions rather than on nominal optimality.

Zopp and Römer [Zopp 02] acoustically optimized the powertrain suspension of a car with respect to the sound pressure distribution inside the vehicle considering requirements of vehicle dynamics. They combined a substructuring method based on frequency response functions (FRF), which is computationally much less expensive than FEM analyses, a weighted sum strategy to meet several design goals simultaneously, and a SQP algorithm in order to reduce the SPL at ear positions by up to 10 dB.

Problems of analysis and optimization of plates and shells were addressed by Awrejcewicz and Krysko [Awrejcewicz 03]. They derived equations for calculating the frequency spectra of shells with transverse deformation and rotary inertia and presented finite approximation solution methods, which were compared with the FEM.

The paper by Bregant and Puzzi [Bregant 03] deals with the optimization of free layer damping treatments to reduce vibration levels of plates. The objective was to maximize the damping level while minimizing the amount of added material. Due to the high number of control variables and multimodal solution spaces with many local optima, a GA was employed, and its performance was compared with that of a SQP method. The amount of material added to a rectangular, simply supported steel plate was not allowed to be more than 10% of the plate's weight; at least 20% of the predefined patches had to be covered.

Fuse et al. [Fuse 03] investigated optimal curvature or rib attachment design for a vibrating aluminum plate. The objective was to reduce the radiated sound power in a frequency band from 50 to 300 Hz using FEM and a GA. The sound power was approximated by the sum of the sound pressure levels computed by the Rayleigh integral at 13 points on a hemisphere above the plate. Nine bending positions were defined along the longer side of the plate, the heights of which were varied by up to ± 1 mm. There were only four peaks in the sound power spectrum of the initial design in the 50-300 Hz frequency band of interest. The optimization process shifted the fundamental frequency beyond the upper frequency limit, thus leading to a quasi-static behavior of the plate within the frequency range of interest. The same or a similar result probably could have been achieved easier by maximizing the fundamental frequency of the plate. An optimized rib design (the total mass of added ribs was not more than 20% of the plate mass) was not able to shift the fundamental frequency beyond the upper frequency limit, thus resulting in a smaller reduction of the radiated sound power than the optimal curvature design.

Michot, Piranda, and Trivaudey [Michot 02] presented a method to optimize simplified models meshed with finite triangular plate elements. Large FE models of a car body typically have about 1 000 000 degrees of freedom (DOFs). The objective was to simplify the mesh by employing some substructuring method, thus reducing the number of DOFs, while preserving the dynamic properties of the structure, i.e., the natural frequencies. A gradient-based algorithm was used to reduce the DOF number of two model structures by a factor of up to 20. The mesh simplification took about two hours of computation time on an HP workstation, but a FE analysis of the simplified model took only 10 seconds instead of 230 seconds for the original model, thus making it suitable for optimization calculations, which usually require a large number of analyses.

Moshrefi-Torbati et al. [Moshrefi-Torbati 03] applied a GA to achieve passive vibration control of a satellite boom structure. The satellite boom was 4.5 m long and constituted a truss made of 93 beams. The geometry of the structure, i.e., the position of the joints, was optimized such that a maximum mid-frequency vibration isolation was achieved. The joints were allowed to move by up to 20% of the length of each bay, i.e., by up to ± 9 cm in all directions. Both the original and the optimized model were built and experimentally tested. The numerical optimization yielded a theoretical vibration isolation of 31 dB within the frequency band 150-250 Hz, which agreed excellently with the experimental results (30 dB attenuation).

Bai and Liu [Bai 04] optimized panel speakers to achieve omni-directional responses at high efficiencies. A GA was used to search for the positions of exciters and the delay of input signals that render optimal performance. A coupled model of panel speakers was developed that incorporated electrical, mechanical, and radiation impedance matrices. The optimization results were verified by experiments according to ISO 3745 in an anechoic room.

1.2.2 Numerical Optimization

Optimization methods have been successfully applied to a number of fields such as economics (profit maximization, effort minimization), structural design (lightweight design, high stiffness, comfort), or traffic of optimization (highways, aircraft, railways). Particularly, the continuous and still ongoing development of cheaper and faster computers facilitates the analysis and optimization of large and complex structures or systems within a reasonable amount of time.

The widespread availability of affordable high-performance personal computers and commercial software has prompted the integration of structural analyses with numerical optimization, reducing the need for design iterations by human designers. Despite its acceptance as a design tool, however, structural optimization seems yet to gain mainstream popularity in industry. To remedy this situation, the paper by Saitou et al. [Saitou 05] reviewed past literatures on structural optimization with emphasis on their relation to mechanical product development, and discussed open research issues that would further enhance the industry acceptance of structural optimization. The past literatures were categorized based on their major research focuses: geometry parametrization, approximation methods, optimization algorithms, and the integration with nonstructural issues.

Rosenbrock [Rosenbrock 60] developed an automatic method for finding the greatest or least value of a function. His technique is based on a modified method of steepest descent. Calculations of gradients or derivatives are not necessary, and the variables can be restricted to a given region. The paper arose from the need to design chemical processes for most economical results, employing five parameters to be optimized. It contains some difficult test cases that later were often used by others (i.e., [Spendley 62, Fletcher 63, Powell 64, Box 65, Corana 87, Powell 94]) as benchmark tests for their algorithms. Powell, Fletcher and Reeves [Powell 62, Fletcher 63, Fletcher 64b, Powell 64] presented several optimization algorithms for finding local minima of functions of several (up to 100) variables, including proofs of convergence. In a review paper, Fletcher [Fletcher 65] compared several derivative-free function minimization techniques. He concluded that Powell's method [Powell 64] was the most efficient.

Price [Price 77] introduced a controlled random search (CRS) procedure for global optimization. Random search and mode-seeking routines were combined into a single, continuous process, which is effective in searching for global optima of a multimodal function with or without constraints. Kirkpatrick, Gelatt Jr., and Vecchi [Kirkpatrick 83] were the first to present the simulated annealing (SA) concept. They developed a combinatorial optimization procedure in a discrete domain and successfully applied it to the traveling salesman problem with 400 cities, to the logic design of an IBM computer chip, and to the optimal placement of computer components (98 chips were to be placed on 100 positions) such that signal propagation times or distances were minimized. SA is a stochastic method, which starts from a user-defined starting point and searches for a minimum in a random direction. If the move was downhill, the new design is accepted and the search proceeds in another random direction. In case the move was uphill, however, it might still be accepted anyway with a certain probability, depending on the size of the uphill step and a parameter called temperature T. That way, the algorithm may escape local minima and finally find the global minimum [Constans 98]. Thus, the SA method couples random function evaluations with a gradually reduced search radius to find the global optimum [Hambric 95]. The algorithm was named after the annealing process. In melted or hot metal, the metal atoms are relatively free to move in random directions. When the temperature is reduced, the atoms are more and more restricted to their positions until they finally "freeze" [Constans 98]. A slow, careful cooling brings the material to a highly ordered, crystalline state of lowest energy, whereas rapid cooling yields defects and glass-like intrusions inside the material [Corana 87]. The algorithm was adapted to problems with continuous variables by Corana et al. [Corana 87]. The adapted version was tested against an adaptive random search method and the Nelder and Mead simplex algorithm [Nelder 1965], using some of Rosenbrock's test functions [Rosenbrock 60]. The SA technique proved to be more reliable than the other methods, but it was quite costly in terms of function evaluations. Goffe, Ferrier, and Rogers [Goffe 94, Goffe 96] applied the SA procedure to the global optimization of statistical functions and performed tests on four econometric problems with up to 62 parameters, comparing the results with those of three conventional algorithms from the IMSL library. SA was very successful in finding optima, whereas the other algorithms failed. The very large number of function evaluations required by the SA algorithm was somewhat compensated by the fact that the other algorithms had to be restarted several times and still were not able to locate the global optimum. A Fortran implementation of the SA algorithm as used by Goffe, Ferrier, and Rogers can be found in [Corana 97].

Public-domain software for black-box global optimization was tested and compared by Mongeau et al. [Mongeau 00]. Techniques such as integral global optimization, GAs, SA, clustering, random search, continuation, Bayesian, tunneling, and multilevel methods were tested on practical problems such as least median of squares regression, protein folding, and multidimensional scaling.

Spellucci's overview article on nonlinear (local) optimization [Spellucci 01] contains 120 references. He addressed some theory, unconstrained minimization, bound constrained problems, general linearly constrained problems (active set methods), linearly constrained problems (interior-point methods), and nonlinearly constrained problems (transformation into an only bound constrained problem, linearization methods, modifications of the SQP method and adaptation of interior-point methods.

An invaluable source of information on optimization algorithms is the continuously updated "Decision Tree for Optimization Software" by Mittelmann and Spellucci [Mittelmann] on the internet. The source code of numerous optimization algorithms can be downloaded for free, and detailed background information is given for each group of problems as well as for suitable solution techniques.

Jianbin Du and Niels Olhoff [Du 07] dealed with topology optimization problems formulated directly with the design objective of minimizing the sound power radiated from the structural surface(s) into a surrounding acoustic medium. The structural vibrations were excited by time-harmonic external mechanical loading with prescribed frequency and amplitude. It was assumed that air is the acoustic medium and that a feedback coupling to the structure can be neglected. Certain conditions were assumed that imply that the sound power emission from the structural surface can be obtained in a simpler way than by solving Helmholz' integral equation. Hereby, the computational cost of the structural-acoustical analysis was substantially reduced. Several numerical results were presented and discussed for plate- and pipe-like structures with different sets of boundary and loading conditions.

1.2.3 Structural Optimization

The focus of the literature review in this section is on structural optimization in general where other than acoustic objectives are used. Only a few selected papers that are relevant to the present work are summarized in this section. For detailed information on structural optimization the reader is referred to textbooks by, e.g., Kirsch et.al. [Kirsch 93], and Bendsøe [Bendsøe 95]. The use of spline functions to reduce the number of design variables as introduced in the present work was first inspired by the paper of Braibant and Fleury [Braibant 84]. They employed B-spline curves to define design elements, making it possible to describe complex geometries by a small set of design variables and just a few design elements.

In a paper by Zhang and Belegundu [Zhang 92] a systematic approach for generating velocity fields in shape optimization was presented. Velocity fields represent the sensitivity of grid points with respect to a design variable and can either be obtained from deformation fields using fictitious auxiliary structures and loads or from a dynamic mode shape analysis.

A review article on the optimal design of mechanical engineering systems was compiled by Papalambros [Papalambros 95] with an emphasis on partitioning, decomposition analysis and decomposition synthesis, and topology design of systems of structural components. In his opinion, the best general purpose optimization codes are based on SQP.

Harzheim, Graf, and Liebers [Harzheim 97] created a program called "Shape200" to create basis vectors for shape optimization using Solution 200 of MSC.Nastran. Previously, deformed shapes were generated using different load cases, and the resulting displacements were used as shape basis vectors. The authors' method uses Bernstein polynomials to define a "shape box".

Sensitivity analysis for sizing optimization using ABAQUS code was the title of a paper by Zhang and Domaszewski [Zhang 98]. They treated ABAQUS as a black box and interfaced its sensitivity analysis capabilities with an optimization algorithm. Information on the element stiffness matrix and the shape functions are not necessary.

Fish and Ghouali [Fish 01] performed multiscale analytical sensitivity analysis for composite materials and investigated the sensitivity of global structure behavior (e.g., deformation or vibration modes) with respect to local characteristics (e.g., material constants). Analytical gradient computation was compared with a central finite difference approximation, which is highly sensitive to the step size.

Kim and Choi [Kim 01] dealt with the direct treatment of a max-value cost function in parametric optimization. In earlier studies, the max-value cost function had been replaced with an artificial design variable leading to an additional equality constraint. However, the direct treatment is more efficient and stable than the transformation treatment and up to 50% faster.

In a paper by Marcelin [Marcelin 01], genetic optimization of stiffened plates and shells was described. The method is based on a GA and uses a back propagation neural network for creating function approximations.

1.2.4 Topology Optimization and Fully Stressed Design

In this section some selected papers and books on topology optimization are covered.

Various techniques for the optimization of structural topology, shape, and material were introduced in a book by Bendsøe [Bendsøe 95] with a focus of topology optimization. The first edition of this book has become the standard text on optimal design, which is concerned with the optimization of structural topology, shape and material. The second edition [Bendsøe 03] has been substantially revised and updated to reflect progress made in modeling and computational procedures. It also encompasses a comprehensive and unified description of the state of the art of the so-called material distribution method, based on the use of mathematical programming and finite elements.

Bakhtiary et al. [Bakhtiary 96] presented a new interface between the FE program MSC.Nastran and CAOSS (computer aided optimization system Sauter), which is based on fully stressed design as well. Duysinx and Bendsøe [Duysinx 98] described a procedure to solve optimal material distribution problems with stress constraints by means of topology optimization of continuum structures.

A detailed review article by Eschenhauer and Olhoff [Eschenhauer 01] has been performed that lists 425 references to papers on topology optimization of continuum structures. It gives an overview of developments within the material technique (microstructure) and geometrical technique (macrostructure) with a special emphasis on optimum topology and layout design of linearly elastic two- and three-dimensional continuum structures.

"Topology optimization - broadening the areas of application" was the title of a paper by Bendsøe et al. [Bendsøe 05]. The focus was on the choice of objective functions and design parametrization for a successful extension of the material distribution approach.

Denli and Sun [Denli 07, Denli 08] reviewed recent advances in the area of composite sandwich modeling, sensitivity analyses, optimization techniques and applications, with the focus on structural acoustic problems. The optimization of sandwich structures was studied with respect to passive design parameters, such as material constants, geometric parameters, cellular core geometry and boundary conditions.

1.2.5 Numerical Acoustics in General

Numerous textbooks deal with more or less general aspects of acoustics and vibration. A report by Müller et al. [Müller 83] introduced simple approximation methods for acoustical calculations.

In his Ph.D. dissertation, Rautert [Rautert 90] both theoretically and experimentally determined bearing loads in spur gears and bevel gears that cause structure borne sound.

A Ph.D. dissertation by Angert [Angert 92] describes investigations of the acoustical behavior of machine structures. The author conducted experimental modal analyses and narrow-band intensity measurements to determine the vibrational behavior of rectangular plates, of a rectangular box, and of an industrial gearbox.

Zopp's Ph.D. thesis [Zopp 00] introduced a FE formulation of aluminum foam structures suitable for the calculation of structure borne sound. Zopp included an approach to optimize the material density distribution of an aluminum foam plate such that all natural frequencies were maximized or, alternatively, such that the first three natural frequencies were minimized while the next three natural frequencies were to be maximized. In the first case the fundamental frequency was increased by almost 25%, whereas in the second case the three lower natural frequencies were reduced by up to 4% and the three upper natural frequencies were increased by up to 14%.

Since the finite element method (FEM) can nowadays be considered a standard tool for engineers to simulate and predict the static and dynamic behavior of structures and systems, this numerical method is not described in the present thesis. Instead, the reader is referred to standard textbooks on FE such as the exhaustive three volume set by Zienkiewicz and Taylor [Zienkiewicz 00] or the book by Bathe [Bathe 96, Bathe 02]. Giljohann [Giljohann 96] introduced FE methods for calculating the sound radiation of arbitrary three-dimensional structures and compared the results of a newly developed method for the calculation of sound radiation into the free field with those of well-known methods. He applied the numerical techniques to an industrial gearbox and achieved good agreement between numerically predicted and experimentally measured values.

A book and some papers by Ihlenburg [Ihlenburg 95, Ihlenburg 98, Ihlenburg 03] deal with the discretization and maximum mesh size required for reliable results of acoustic FE calculations. According to these references, one needs an extremely refined mesh for medium and high wave numbers in order to avoid "numerical pollution" effects caused by the fact that "numerical waves" are dispersive also in nonassertive media, i.e., the discrete wave number in an FE model depends on the frequency due to discretization. Therefore, the "rule of thumb" of ten elements per wavelength leads to inaccurate results due to meshes that are too coarse.

General numerical methods and algorithms are described in detail, for instance, in the book by Engeln-Müllges and Uhlig [Engeln-Müllges 96] and in the famous "Numerical Recipes" books by Press et al. [Press 92, Press 96]. All three books contain numerous computer routines in Fortran source code.

Finite Element Mesh Refinement, Coarsening, and Adaptation Initially, it was also considered to employ mesh adaptation techniques to reduce the number of design variables and computation time. It turned out, however, that, as for the topology optimization and fully stressed design techniques, it was not possible to derive criteria to determine at which locations of a structure the FE mesh is to be refined or coarsened. This is due to the frequency dependence of computed quantities and to the various local thickness modifications that occur while the optimization is in progress. Furthermore, "mesh refinement is not suited in this case since this would cause discontinuities of the objective function" [Fritze 03]. Thus, after each mesh adaptation, the optimization procedure would have to be restarted, which is impractical.

A series of paper were published by Bös and Nordmann [Bös 02a, Bös 02b, Bös 03b, Bös 03a, Bös 06] on the numerical structural optimization with respect to structure borne sound. They used various spline formulations and objective functions to reduce the radiated sound power from the several structures. Bös in his Ph.D thesis [Bös 04] described a numerical method to optimize the thickness distribution of three-dimensional structures with respect to various vibrational and structural properties. A combination of a commercially available finite element (FE) software package and additional user-written programs was used to modify the shape (but not the number of nodes and elements) of FE models of the structures to be optimized. The design variables were the structure's local thickness values at selected surface nodes. Possible objectives of the optimization included the minimization of the vibration level, the minimization of the structural mass, the maximization of the fundamental frequency, and the maximization of the difference between two arbitrarily chosen natural frequencies. The optimization procedure was applied to three example structures, namely, a rectangular plate, two plates joined at 90ř, and a gearbox. Depending on the particular structure and on the choice of the objective function and constraints, the vibrational and structural properties can be substantially improved.

Ranjbar et al. [Ranjbar 06,Ranjbar 07b,Ranjbar 07a,Ranjbar 10] presented several works on the comparison of optimization and approximation methods with respect to the structural acoustics applications. They showed that some optimization and approximation methods are more suitable for developing of hybrid robust optimization algorithms.

1.2.6 Active Control

Some references related to active control of sound and vibration are cited here as well, even though only passive vibration control by means of structural optimization is considered in the present work. This is done because they employ some of the methods described in the previous sections.

Introductory and advanced textbooks on active noise or vibration control were written by Nelson and Elliott [Nelson 92], Fuller, Elliott, and Nelson [Fuller 96], Hansen and Snyder [Hansen 1996], Snyder [Snyder 2000], Hansen [Hansen 2001], and Preumont [Preumont 02]. Cunefare and Koopmann [Cunefare 91b] considered both surface and far-field effects when they applied active noise control to achieve a global minimum of sound power radiated from a box structure with active sources.

Naghshineh and Koopmann [Naghshineh 94] developed an active control strategy for achieving weak radiator structures. They employed an interesting twist on the weak radiator concept by using active vibration control to force a beam to vibrate as a weak radiator. A set of control forces that resulted in minimum radiated sound power was found by means of numerical optimization. The effect of the number and location of the actuators on sound power level reductions was studied as well.

"Natural algorithms", i.e., several genetic and simulated annealing algorithms, were developed by Baek and Elliott [Baek 95] and tested as methods of finding optimal secondary loudspeaker positions in an active noise control system. They compared the performance of these algorithms with that of a simple random search. The best GA and the best SA algorithm exhibited a similar convergence speed. The numerical results agreed well with experimental results. The methods seemed to be reasonably robust for slight frequency changes.

1.3 Hybrid Robust Shape Optimization

Optimization techniques have been applied to versatile engineering problems for reducing manufacturing cost and for automatic design. The main functional requirement of a mechanical system is to obtain the target performance with maximum robustness.

The deterministic approaches of optimization neglect the effects from uncertainties of design variables. The uncertainties include variation or perturbation such as tolerance band. At optimum, the constraints must be satisfied within the tolerance ranges of the design variables. The variation of design variables can also give rise to drastic change of performances. The two issues are related to constraint feasibility and insensitive performance.

The current trend of design methodologies is to make engineers objectify or automate the decision making process. Numerical optimization is an example of such technologies but it may produce uncontrollable uncertainties. To increase manageability of such uncertainties, the Taguchi method, reliability-based optimization and robust optimization are commonly being used.

Robust optimization is an approach in optimization to deal with uncertainty. A robust optimization should be problem independent. Popular robust algorithms are Genetic Algorithms and Evolutionary Algorithms, Hybrid Algorithms and Approximation based methods.

Genetic and evolutionary algorithms are based on principle of survival of the fittest. They are usually able to find the global minimum and can avoid local minima. They can handle all types of discontinuities. The most deficiencies of these methods are that they require many function evaluations and they need extensive tuning for their parameters.

Hybrid algorithms use a combination of algorithms plus a switching strategy for searching design space. Such algorithms may include gradient search method, a genetic algorithm (GA), the Nelder-Mead simplex method, etc. These algorithms are computationally efficient for problems with several local minima. Furthermore, they can be used for some problems with robustness due to use of gradient search. However, they requires esoteric heuristics based switching rules that are problem based. Also, they require a flexible software architecture so that the users can implement custom strategies easily.

Approximation-based methods construct of surrogate models (response surfaces) that can be evaluated quickly. They are computationally efficient and robust. Most of these methods don't scale well like quadratic response surface modeling which requires n^2 samples to build the approximation for an objective function with n variables. Kinds of approximations are Kriging (moving least squares), Polynomial (cubic, quadratic), Neural Networks (NN), Multivariate Regression Splines and many others.

The optimization method basically works as follows: Build initial approximation based on a given sample set, Use stochastic optimization method to find the minimum of the approximation to get a new design, Evaluate the new design with the full analysis code, Use the new results to improve the accuracy of the approximation in the local search area and continue until termination criterion is met.

Shim and Manoochehri [Shim 99] presented a computer-based shape configuration design methodology to generate optimum design of specified structures satisfying the structural performance requirements and the geometric connectivity of the model. Mathematically, this problem can be categorized as a large-scale, nonconvex and nonlinear problem. The solution methods, grouped into two main categories, deterministic and stochastic approaches, require enormous computational efforts to find global optimum designs, a matter of major importance since many local suboptimal solutions can exist. They examined and compared two popular methods belonging to each class. The methods understudied were selected as the enumeration technique for deterministic approach and the simulated annealing for the stochastic method. The advantages and disadvantages of each technique were investigated. Using the best properties of each method and an algorithm for phase change between the two, a hybrid global shape optimization approach was formulated. The hybrid method was structured to combine the enumeration method for local minimization process and the simulated annealing for global minimum search phase. The hybrid method could find global optimum designs in a robust and efficient way.

Lee and Park [Lee 01] developed a robust optimization method to obtain an optimum value insensitive to variations on design variables within a feasible region. This was performed by using a mathematical programming algorithm. A multiobjective function was defined to have the mean and the standard deviation of the original objective function, while the constraints were supplemented by adding a penalty term to the original constraints. This method had an advantage in that the second derivatives of the constraints were not required. Several standard problems for structural optimization were solved to check the usefulness of the suggested method.

Xu [Xu 03] developed a multi-dimensional hybrid global optimization method. The method consisted of two basic components: local optimizers and feasible point finders. Local optimizers guarantee efficiency and speed of producing a local optimal solution in the neighborhood of a feasible point. Feasible point finders provide the theoretical guarantee for the new method to always produce the global optimal solution(s) correctly.

McAllister and Simpson [McAllister 03] introduced a multidisciplinary robust design optimization formulation to evaluate uncertainty encountered in the design process. The formulation is a combination of the bi-level collaborative optimization framework and the multiobjectives approach of the compromise decision support problem. To demonstrate the proposed framework, the design of a combustion chamber of an internal combustion engine containing two subsystem analyses was presented. The results indicated that the proposed collaborative optimization framework for multidisciplinary robust design optimization effectively attains solutions that were robust to variations in design variables and environmental conditions.

Gunawan [Gunawan 05] presented a robust optimization method that ensured feasibility of an optimized design when there were uncontrollable variations in design parameters. This method was developed based on the notion of a sensitivity region. In this method, as the design moves further inside the feasible domain, and thus becoming more feasibly robust, the sensitivity region becomes larger. This method was not sampling based so it did not require a presumed probability distribution as input and was reasonably efficient in terms of function evaluations. In addition, this method did not use gradient approximation and thus was applicable to problems that have non-differentiable constraint functions and large parameter variations.

Lee and Park [Lee 06] developed a design procedure for global robust optimization using kriging and global optimization approaches. Robustness was determined by kriging model to reduce a number of real functional calculations. The simulated annealing algorithm was adopted to determine the global robust optimum of a surrogate model. As the postprocess, the global optimum was further refined by applying an approximation method.

Yildiz et al. [Yildiz 07] presented a hybrid optimization approach, which deal with the improvement of shape optimization process. The objective was to contribute to the development of more efficient shape optimization approaches in an integrated optimal topology and shape optimization area with the help of genetic algorithms and robustness issues. An improved genetic algorithm was introduced to solve multiobjective shape design optimization problems. The specific issue of this research was to overcome the limitations caused by larger population of solutions in the pure multiobjective genetic algorithm. The combination of genetic algorithm with robust parameter design through a smaller population of individuals resulted in a solution that leaded to better parameter values for design optimization problems. The effectiveness of the proposed hybrid approach was illustrated and evaluated with test problems taken from literature. It was also shown that the proposed approach could be used as first stage in other multiobjective genetic algorithms to enhance the performance of genetic algorithms. Finally, the shape optimization of a vehicle component was presented to illustrate how the present approach could be applied for solving multiobjective shape design optimization problems.

Mönnigmann et al. [Mönnigmann 07] proposed a novel approach for the parametrically robust design of dynamic systems. The approach could be applied to system models with parameters that were uncertain in the sense that values for these parameters were not known precisely, but only within certain bounds. The novel approach was guaranteed to find an optimal steady state that was stable for each parameter combination within these bounds. Their approach combined the use of a standard solver for constrained optimization problems with the rigorous solution of nonlinear systems. The constraints for the optimization problems were based on the concept of parameter space normal vectors that measure the distance of a tentative optimum to the nearest known critical point, i.e., a point where stability may be lost. Such normal vectors were derived using methods from nonlinear dynamics. After the optimization, the rigorous solver was used to provide a guarantee that no critical points exist in the vicinity of the optimum, or to detect such points. In the latter case, the optimization is resumed, taking the newly found critical points into account. This optimize-and-verify procedure was repeated until the rigorous nonlinear solver could guarantee that the vicinity of the optimum was free from critical points and therefore the optimum was parametrically robust. In contrast to existing design methodologies, this approach could be automated and did not rely on the experience of the designing engineer.

1.4 Scope and Objectives of this Study

This section describes the scope and objectives of this dissertation. The issues that are objectives and the issues that are not objectives are discussed in Sec. 1.4.1 and Sec. 1.4.2, respectively. Then in Sec. 1.4.3 , some open research areas are presented. Finally, the outline of this thesis is explained in Sec. 1.5.

1.4.1 Issues that are Objectives

The objectives of the present research, which can be derived partially from the previous literature review, can be described as follows:

- The main objective of this study is the comprehensive performance investigation of various optimization and approximation methods for the numerical geometry modification of three-dimensional structures with respect to vibrational or structural properties. A combination of commercial FE software, user-written Fortran, C and C++ routines, and Unix shell scripts that automatically optimizes the geometry in an iterative manner with respect to an objective function and subject to considered constraints, is developed. The objective function includes the root mean square level of structure borne sound (RMSL). Possible candidates for constraint include upper and lower bounds on design variables (i.e., local geometry modification values) and structural mass.

- In many of former publications the symmetry of FE models was exploited, i.e., only one half or even one quarter of the actual structure was modeled, thus significantly reducing computation time and the number of design variables. In the present work, however, no such simplifications are made.

- Most of previous studies used a rather moderate number of design variables ranging from four to eight. Hardly ever was this number greater than ten. Marburg and Hardtke [Marburg 02f] consider 44 design parameters a "large number" or, at another place in the same paper, even "huge number of parameters". In the present dissertation, a moderate number of nine design variables considered for the geometry modification of the rectangular plate.

- Many researchers chose the relatively narrow frequency ranges of interest for optimization calculations, which drastically reduce computation times. Extreme cases with a frequency bandwidth of 100 Hz or less include, e.g., [Keane 95]: 150-250 Hz, [McMillan 97]: 100-110 Hz, [Moshrefi-Torbati 98]: 55-65 Hz, [Ratle 98]: 50-70 Hz (but also 0-600 Hz), [Marburg 2002b]: 0-100 Hz, or [Moshrefi-Torbati 03]: 150-250 Hz. Examples for medium frequency bandwidths between 100 and 1000 Hz can be found in [Lamancusa 88]: 50-250 Hz, [Lamancusa 91]: 0-800 Hz and 0-1000 Hz (but also 200-2000 Hz), [Inoue 93]: 500-1500 Hz, [Lamancusa 93]: 0-1000 Hz, [Marburg 97b]: 0-200 Hz, [Ratle 98]: 0-600 Hz, [Marburg 02f]: up to 200Hz, [Fritze 03]: 0-250 Hz, or [Fuse 03]: 50-300 Hz (ten lowest modes). For all of the optimization runs presented in this dissertation, a frequency band of interest ranging from 0 to 100 Hz is chosen in order to avoid excessive computation time. An advantage of using such frequency bandwidth is the fact that the FE model must not be discretized by a very refined mesh so as to avoid longer computation times. For a detailed discussion on this issue the reader is referred to Sec. 5.4.

- Most of the previously published papers do not contain statements concerning the number of iterations required by the optimization algorithm to reach convergence or at least to achieve an improved design. Exceptions include, for instance, [Lamancusa 93], [Hambric 95], and [Hinton 95b]. Some other researchers, e.g., [Pritchard 87], [Grandhi 92], [Lamancusa 93], [Moshrefi-Torbati 98], [Tinnsten 99], [Tinnsten 00], [Kaneda 02], [Michot 02], or [Bös 06] stated the number of iterations implicitly by providing iteration history plots, i.e., line graphs showing the objective function or some other quantity vs. the number of iterations. Often, it is not clear if the reported number of iterations is the true number of objective function evaluations, i.e., including the number of function evaluations required for the sensitivity analysis, or just the much lower number of combined objective function and sensitivity calculation steps. For genetic algorithms, [McMillan 97], [Bregant 03] presented iteration history plots in terms of generations. This form of representation obscures the true number of design or function evaluations somewhat (one generation can stand for hundreds of function evaluations) and may therefore appear more advantageous. Bregant and Puzzi [Bregant 03] did not even give the number of individuals per generation, thus making it impossible to assess the performance and efficiency of their approach. For the present study, all iteration histories were thoroughly recorded and reported in detail.

- Quite often, particularly in industrial applications, a limited number of design variations that yield some improvement is called an optimization. In this dissertation, mathematical optimization techniques in the true sense of the word best optimum were employed to find the best solution of all possible solutions. Since the computational effort to obtain a global optimum can be extremely high, it is considered sufficient to find a local optimum that yields a significant improvement compared to the initial design. Marburg et al. [Marburg 97a] were of the opinion that achieving a decrease of 3 dB is considered successful. In another paper [Marburg 02f], Marburg and Hardtke admitted that "we can be sure that we will not find the global optimum. However, for technical requirements a significant improvement of the objective function in a certain period of time is more important than a long or almost infinite search for the global optimum". In this dissertation, all of the possible local and global minima by different optimization methods are searched. In some cases, an objective function improvement around 23 dB is reported.

1.4.2 Issues that are not Objectives

The following issues are not objectives of the present research project:

- The numerical structural acoustic optimization method introduced in the present study does not employ active noise or vibration control strategies, but is solely based on design modifications of structures for passive noise or vibration control. Keane [Keane 95] stated that active vibration control measures are inevitably expensive to install and maintain, and passive solutions would be preferable if they could be found. Kaneda et al. [Kaneda 02] expressed their opinion that passive measures such as use of plate thickness, added masses, damping materials, and ribs or other stiffeners are still an attractive alternative [compared to active noise control] for reason of economy, simplicity, and stability.

- No experimental measurements were performed to verify the numerical results. The prime reason for that is simply lack of time. In the present case, performing experiments properly is considered quite costly in terms of both time and money. The optimized designs would have to be manufactured by means of some computer controlled techniques, and an appropriate test stand would have to be designed and built.

- Neither material strength nor manufacturability issues are considered. It should be checked if the optimized structures can withstand given static and dynamic loads. Of course, designs optimized with respect to certain vibrational or structural properties are worthless if they fail when subjected to operating conditions. Likewise, it should be investigated and ensured that an optimal design can be manufactured at reasonable cost. If it is not manufacturable at all or only at very high costs, it is impractical as well.

- Only the structure borne sound is considered but not air borne or radiated sound, i.e., the total sound power radiated from the structure.

- It is not an objective to find optimal realistic designs, but rather to create design proposals that may be redesigned and adapted to real applications. The design proposals can also serve to gain some insight in the behavior of a structure. This approach is supported by a statement by Hinton, Q̈zakça, and Rao [Hinton 95b]: "Although some of the optimal shapes of the structures obtained may look impractical, they serve as a guide to designing practical shapes and as an educational tool."

1.4.3 Open Research areas

After careful reviewing of the previous works in the field of structural acoustic optimization, some open research fields are experienced as

- There is a lack of exhaustive comparative study on the performance, advantages and disadvantages of various types of optimization and approximation algorithms and their combinations for the numerical geometry modification in structural acoustics.

- Although structural acoustic optimization processes are time consuming but there is no guaranty to achieve the desire optimum after performing a certain number of function evaluations. Therefore, finding of some powerful optimization algorithms with respect to their convergence rate, accuracy and robustness level for structural acoustics application is still an open research area which must be more investigated. Some questions about the necessity and manner of usage of hybrid robust optimization algorithms in structural acoustics, e.g., the type of switching strategies and the appropriate number of optimization steps in a multi-stages hybrid robust optimization algorithm, must be clarified.

The contribution of the present Ph.D. work is to explore these open research areas and find some appropriate answers for these questions.

1.5 Outline

The remainder of this dissertation is organized as follows:

In Chap. 2 some theory on structural acoustics is provided. Section 2.1 introduces the fundamental equation of machine acoustics. The calculations of the level of structure borne sound and the root mean square level of structure borne sound are described in Sec. 2.2.

Chapter 3 first gives a general overview on the numerical optimization and approximation methods considered in this study, namely, Simulated Annealing, Tabu Search, Genetic Algorithms, Controlled Random Search Method, Method of Feasible Directions, Limited Memory Broyden-Flecher-Goldfarb-Shanno Algorithm for Bound Constrained Optimization, Sequential Quadratic Programming Method, Newton Method, Method of Moving Asymptotes, Mid-Range Multi-Points Method, Hybrid Neural Networks including a Simulated Annealing Algorithm and finally a Hybrid method including method of Design of Experiments and Simplex method.

A detailed description of the optimization procedure in general (Sec. 4.1) and using either of optimization and approximation techniques in particular are given in later sections of chapter 4.

Chapter 5 introduces the finite element model, namely, a rectangular plate, and the frequency discretization approach which is used for the dynamic analysis.

Chapters 6 presents various optimization results for the rectangular plate.

Finally, Chapter 7 discusses on some conclusions as well as suggestions for the future work.

Chapter 2

Structural Acoustics

This chapter provides some theory on structural acoustics required for the optimization calculations presented in the subsequent chapters. In Sec. 2.1, the fundamental equation of machine acoustics is introduced. Then, Section 2.2 describes the calculation of the root mean square level of structure borne sound from the root mean square of the surface velocity vectors obtained from a FE analysis.

2.1 Fundamental Equation of Machine Acoustics

A reliable and well-known measure for the noise emitted from some structure or machine part is the level of radiated sound power $L_P(\omega)$, or sound power level for short, which is a function of circular frequency ω,

$$L_P(\omega) = 10 \ \mathrm{lg} \frac{P(\omega)}{P_0} \ \mathrm{dB}, \tag{2.1}$$

where $P(\omega)$ is the radiated sound power and $P_0 = 10^{-12}$ W is a standardized reference value. The radiated sound power $P(\omega)$ in turn can be calculated by [Kollmann 00]

$$P(\omega) = \rho_a c_a \ S\overline{v^2_{\perp rms}(\omega)}\sigma(\omega). \tag{2.2}$$

Here, ρ_a and c_a are the density and the speed of sound of the surrounding fluid (in this case air), respectively, S is the area of the sound radiating surface, $\overline{v^2_{\perp rms}(\omega)}$ is the mean squared normal velocity of the surface averaged over the radiating surface, and $\sigma(\omega)$ is the radiation efficiency. The quantity $Z_a = \rho_a c_a$ is the so-called specific impedance of air.

By introducing the so-called mean squared transmission admittance [Kollmann 00]

$$h_t^2(\omega) = \frac{v^2_{\perp rms}(\omega)}{F^2_{rms}(\omega)}, \tag{2.3}$$

where $F_{rms}(\omega)$ is the rms excitation force, Eq. (2.2) can be rewritten as

$$P(\omega) = \rho_a c_a \ S\sigma(\omega) h_t^2(\omega) F^2_{rms}(\omega), \tag{2.4}$$

which is considered the fundamental equation of machine acoustics [Kollmann 2000]. In level notation, Eq. (2.4) becomes

$$L_P(\omega) = L_\sigma(\omega) + L_{Sh_t^2}(\omega) + L_F(\omega), \tag{2.5}$$

where $L_\sigma(\omega)$ is the level of radiation efficiency, $L_{Sh_t^2}(\omega)$ is the so-called level of structure borne sound (LS), and $L_F(\omega)$ is the level of the excitation force. The level of the specific impedance $\rho_a c_a$ in Eq. (2.4) vanishes because the standardized reference value for the calculation of the level is equal to the specific impedance of air at normal temperature and air pressure $(\rho_a c_a)_0 = \rho_a c_a \approx 414$ Ns/m. Since $\rho_a c_a$ and its reference value $(\rho_a c_a)_0$ are identical, the argument of the logarithm becomes unity and, thus, the logarithm itself becomes zero.

From Eq. (2.5), it can be seen that the radiated sound power level $L_P(\omega)$ can be interpreted as the sum of three contributing levels, namely, $L_\sigma(\omega)$, $L_{Sh_t^2}(\omega)$, and $L_F(\omega)$. Hence, the radiated sound power can be reduced if all three contributing levels are reduced or if one or two of the contributing levels are decreased as long as the remaining ones do not overcompensate this by a drastic increase.

Whereas measures to reduce the excitation forces (L_F) generally do not influence the vibrational ($L_{Sh_t^2}$) or radiational behavior (L_σ) of a structure, measures to lessen the vibrational level always do have an influence on the radiation efficiency and vice versa [Kollmann 00]. There are cases where the vibrational and the radiational behavior exhibit contrary tendencies, i.e., a decrease of structure borne sound can sometimes lead to increased acoustic radiation and vice versa. However, the measures that influence the vibrational behavior, i.e., structure borne sound, in a positive way have the greatest potential to reduce radiated sound power levels [Kollmann 00]. This is because there is an upper limit on the frequency dependent radiation efficiency $\sigma(\omega)$, namely, the radiation efficiency of a monopole radiator. Theoretically, in certain cases the radiation efficiency of a rectangular plate at the coincidence frequency can exceed that of a monopole radiator by up to 5 dB. For practical applications, however, this is irrelevant. In contrast, there is no equivalent lower bound on the level of structure borne sound, so it can be further reduced even when the radiation efficiency is at its upper limit.

Therefore, only structure borne sound is considered in this thesis. This has the advantageous side-effect that fast, simple dynamic structural FE calculations suffice to compute the level of structure borne sound, whereas more complicated and quite time-consuming boundary element method (BEM) or infinite element method (IEM) computations would be necessary to determine the radiated sound power.

2.2 Root Mean Square Level of Structure Borne Sound

The level of the structure borne sound $L_{Sh_t^2}(\omega)$ in Eq. (2.5), which is from now on referred to as LS for convenience, can be interpreted as a measure of the vibrational sensitivity of the structure when subjected to some excitation. It can be calculated from [Kollmann 00]

$$LS = L_{Sh_t^2}(\omega) = 10 \text{ lg} \frac{Sh_t^2(\omega)}{S_0 h_{t0}^2} \text{ dB}, \tag{2.6}$$

where $S_0 h_{t0}^2 = 2.5 \cdot 10^{-15}$ m^4/(N^{2}s^2) is a standardized reference value. From Eq. (2.6), the LS can be interpreted as the level of the mean squared transmission admittance $h_t^2(\omega)$ in Eq. (2.3) that is weighted with the surface area of the sound radiating surface S before taking the logarithm.

In order to calculate the mean squared transmission admittance $h_t^2(\omega)$ according to Eq. (2.3), which is an ingredient for the LS in Eq. (2.6), the mean squared rms normal velocity of the surface averaged over the radiating surface $v_{\perp rms}^2(\omega)$ must be determined.

The rms velocity vector $v_{rms\imath}(\omega)$ at some point $\imath$ on the sound radiating surface can be obtained either from an experimental measurement using accelerometers or a laser vibrometer, or numerically from a dynamic FE analysis. Either way, the component of the rms velocity vector $v_{rms\imath}(\omega)$ that is normal to the surface $v_{\perp rms\imath}(\omega)$ is then calculated by

$$v_{\perp rms\imath}(\omega) = v_{rms\imath}(\omega) \cdot \mathbf{n}_\imath, \tag{2.7}$$

where $\mathbf{n}_\imath$ is the unit normal vector on that particular surface point $\imath$.

Once the rms normal surface velocity distribution at the nodal points of the some measurement mesh on the structure's surface or of the some FE discretization is known, the mean squared rms normal surface velocity averaged over the radiating surface

$$\overline{v^2_{\perp rms\imath}(\omega)} = \frac{1}{\mathbf{n}_n} \sum_{i=1}^{\mathbf{n}_n} v^2_{\perp rms}(\omega), \tag{2.8}$$

where $\mathbf{n}_n$ is the number of the measurement points or FE nodes on the surface of the structure, can then be calculated, provided that the measurement or FE mesh is rather uniform. Thus, the LS in Eq. (2.6) can be determined from the nodal rms surface velocity vectors $v_{rms\imath}(\omega)$ by combining Eqs. (2.7), (2.8), and (2.3).

A detailed description of the experimental measurements or of the FEM used to obtain the nodal rms surface velocity vectors $\mathbf{n}_\imath$ is beyond the scope of this work and can be found elsewhere in the literature (e.g., [Bathe 96, Bathe 02, Cremer 88, Cremer 96, Kollmann 00, Zienkiewicz 00]). It is worth noting, however, that in the present dissertation the velocity vectors $v_{rms\imath}(\omega)$ are solely calculated by means of the FEM using a modal superposition technique, which is admissible for lightly damped structures. This means that each FE analysis consists of the two consecutive steps: The first step is a numerical modal analysis, which determines the natural frequencies and the mode shapes of the structure. This step is called “natural frequency extraction” in the FE software ANSYS [ANSYS]. In the second step, called “mode based steady-state dynamic analysis” in ANSYS, the velocity vectors $v_{rms\imath}(\omega)$ are obtained by superposition of the previously computed mode shapes using scalar mode participation factors [Zienkiewicz 00, ANSYS]. The mode participation factors can be regarded as weighting factors, which show the proportions of the each mode occurring [Zienkiewicz 00]. The numerical modal analysis in the first step ensures that all natural frequencies and mode shapes in the frequency band of the interest are automatically taken into account and none can be missed when the vibrational response of the structure subject to some force excitation is calculated in the second step. Previous studies used constant frequency increments of 10 Hz [Inoue 93, Kaneda 02] or 2 Hz [Marburg 97a], which contains the risk of missing some resonance peaks and requires long computation times due to the refined frequency resolution. The technique employed in the present work is explained in more detail in Sec. 5.1.

Since acoustic power is determined by the surface velocity, one alternative and less computationally expensive objective function is to consider only vibrational efficiency of the structure as expressed by the mean square normal velocity [Lamancusa 93].

The LS in Eq. (2.6) constitutes a spectrum, i.e., it is a function of the circular frequency ω. To obtain some single global measure of the vibrational behavior of the structure in a given frequency range of interest, the root mean square level of the structure borne sound over that frequency band, known hereafter as RMLS, is calculated.

$$\mathrm{RMSL} = \sqrt{\frac{\int_{\omega_{min}}^{\omega_{max}} LS^2(\omega) d\omega}{\omega_{max} - \omega_{min}}} \ \mathrm{dB} \tag{2.9}$$

In Eq. (2.9), ω_{max} and ω_{min} are the lower and upper bounds of the circular frequency range under consideration, respectively. The RMLS is the root square of the area beneath the LS spectrum divided by the width of the frequency band and can be computed numerically by means of, e.g., the trapezium integration rule [Zopp 00]. It can be considered a special quantity characterizing the vibrational energy contained in the given frequency range. It serves as the objective function in the optimization problem presented in this dissertation.

Chapter 3

Optimization and Approximation Algorithms

The first section of this chapter describes, a general optimization problem as well as various possible classifications to which optimization algorithms can be assigned. Then, the following two sections introduce and describe the optimization and approximation algorithms used in this study and provide some rationale for preferring these numerical optimization techniques.

3.1 General Aspects of Numerical Optimization Algorithms

Optimization is defined as the minimization or maximization of an objective function subject to constraints on its variables [Nocedal 99]. Usually, the following notation is applied:

- The variables ϑ_i ($i = 1,\ 2, \ldots,\ n;\ i,\ n \in \mathbb{N}$), which are varied in order to find the minimum or maximum, are the design variables, also called design parameters. These n design parameters form the vector of design variables $\boldsymbol{\vartheta}$.
- The function of the vector of design variables $\mathcal{F}(\boldsymbol{\vartheta})$ that is to be minimized or maximized is called the objective function.
- The individual restrictions $c_j(\boldsymbol{\vartheta})$ ($j = 1,\ 2, \ldots,\ m;\ j, m \in \mathbb{N}$) that are placed on the variables $\boldsymbol{\vartheta}$ are called the constraints, which form the vector of constraints $\mathbf{c}(\boldsymbol{\vartheta})$. The set of points $\boldsymbol{\vartheta}$ that satisfies all of the m constraints $c_j(\boldsymbol{\vartheta})$ is called the feasible region, and any vector of design variables $\boldsymbol{\vartheta}$ that lies within the feasible region is called a feasible design.

A general optimization problem can then be formulated as

$$\text{minimize } \mathcal{F}(\boldsymbol{\vartheta}),\ \ \boldsymbol{\vartheta} \in \mathbb{R}^n, \tag{3.1a}$$

$$\text{subject to} \begin{cases} \mathbf{c}_{eq}(\boldsymbol{\vartheta}) & = \mathbf{0} \\ \mathbf{c}_{ineq}(\boldsymbol{\vartheta}) & \geq \mathbf{0}\ , \end{cases} \tag{3.1b}$$

where $\mathbf{c}_{eq}(\boldsymbol{\vartheta})$ are equality constraints and $\mathbf{c}_{ineq}(\boldsymbol{\vartheta})$ are inequality constraints. The objective function $\mathcal{F}(\boldsymbol{\vartheta})$ can be maximized by minimizing $-\mathcal{F}(\boldsymbol{\vartheta})$. Likewise, inequality constraints of the form $\mathbf{c}_{ineq}(\boldsymbol{\vartheta}) \leq 0$ can be written as $-\mathbf{c}_{ineq}(\boldsymbol{\vartheta}) \geq 0$.

Optimization methods can be categorized by various criteria. The following list can give an impression of the numerous existing categories.

- *deterministic vs. stochastic*: Deterministic methods create new designs or trial solutions based entirely on the results and the success of previous iterations by interpolation, extrapolation, calculation of gradients, etc. Stochastic optimization techniques involve at least some degree of randomness and probability, ranging from a minor or moderate influence of heuristic procedures on parameters controlling the optimization process to completely random searches.

- *local vs. global*: Local optimization algorithms may get trapped in a local optimum and hence fail to find the global optimum of an optimization problem. Remedies against this shortcoming include skillfully choosing a suitable initial design that is close to the assumed or actual global optimum, or restarting the optimization procedure several times in succession with various different initial designs. If most or all of the successive runs result in the same optimum it can be assumed that the global optimum was found. Global optimization procedures are designed always to find the global optimum. They contain mechanisms and strategies that enable them to escape local optima and explore other regions of the design space. Most of the global optimization methods (at least all of the methods known to the author) are stochastic methods. Figure 3.1 illustrates the concept of local and global extremum by means of some arbitrary function $\mathcal{F}(\vartheta)$ of one variable ϑ. In this example, the global minimum is located left near to the lower limit of the feasible design space, whereas the global maximum is situated somewhere in the middle of the feasible interval.

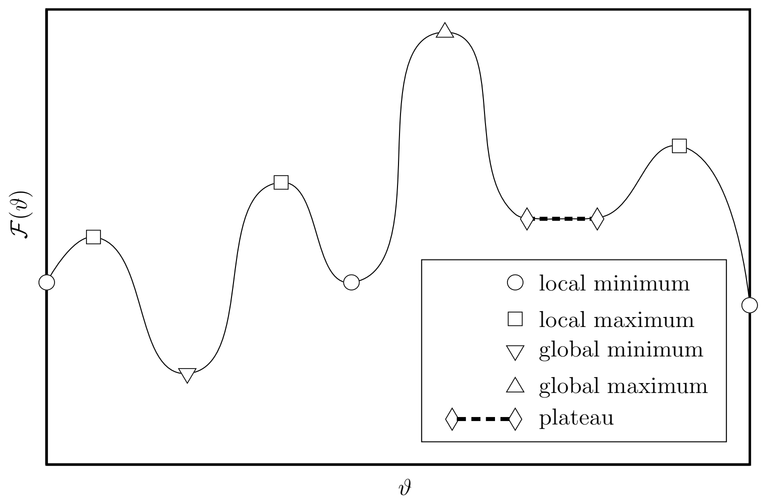

Figure 3.1: Examples of local and global extrema of some arbitrary function $\mathcal{F}(\vartheta)$.

- *unconstrained vs. constrained*: Unconstrained optimization problems are of rather theoretical and mathematical nature. Unconstrained means that there are no restrictions at all to the design parameters or to the objective function values|they can take any value they want to. Most real-life optimization problems are constrained meaning that one or more restrictions apply. For instance, the cross-sectional area of a beam cannot become negative, some physical properties such as mass or density are always nonnegative, the total cost of a product shall not exceed a certain limit, etc.

- *linear vs. nonlinear*: If the objective function and all of the constraints are linear functions of the design parameters, the optimization problem is said to be a linear one. Numerous specialized and highly efficient algorithms exist for this particular class of problems. General nonlinear optimization problems (in which some or all objective or constraint functions may be nonlinear functions of the design variables) are somewhat more difficult to solve and require some special nonlinear optimization techniques. A special subcase of the nonlinear class is the quadratic optimization problem for which specialized strategies are available as well.

- *continuous vs. discrete*: Continuous optimization problems are characterized by design variables and objective function values that can take any real number that does not violate any constraints. Discrete optimization involves design variables and objective function values that are integer or even natural numbers. Examples for discrete optimization include standardized design variables (e.g., standardized cross-sectional dimensions of steel girders or bolts), the number of parts produced (it is not sensible to take half light bulbs or half cars into account), or the well-known traveling salesman problem, i.e., finding the shortest route to visit a given number of cities and finally returning to the starting point without visiting any city more than once.

- *analytical vs. numerical*: Kirsch [Kirsch 1993] distinguishes between analytical and numerical optimization. Analytical optimization strategies employ the mathematical theory of calculus, variational methods, etc. The optimum solution is theoretically found exactly by solving a system of equations that express the optimality conditions. With numerical procedures a near optimal solution is automatically generated in an iterative manner. An initial guess serves as a starting point for a systematic search for better designs that is terminated when predefined criteria are satisfied.

- *shape vs. topology*: Particularly in structural optimization, one can differentiate between shape and topology optimization [Baier 94, Bendsøe 95]. Shape optimization techniques can only modify the outer shape of a structure (thickness, radiuses, curvatures, etc.) but cannot remove any material from the inside of the structure (wholes, branches, etc.). Topology optimization "thins out" and finally removes material on the inside or at the edge of a structure at places where it is not really needed in order to withstand a given load (low stress regions). The result often looks like a truss or framework.

- *approximate vs. exact*: Approximate optimization algorithms are those that use either an approximated value of objective function, or approximated values for the first and second derivatives of the objective function. In contrary, exact optimization methods use the exact value of objective function without any approximation.

Based on this classification scheme of optimization techniques, the algorithms used in the present work can be categorized as constrained, nonlinear, continuous, and numerical, and are used to perform shape optimization. However, some of them, namely, MFD, SQP, MMA, MMP, L-BFGS-B and NM, are considered as deterministic, local and approximate, whereas some of them, i.e., GA, TS, CRSM and SA, are considered as stochastic, global and exact.

3.2 Optimization Methods

Figure 3.2 shows the local and global optimization methods which are considered for this comparison study. The performance of these methods will be investigated and reported.

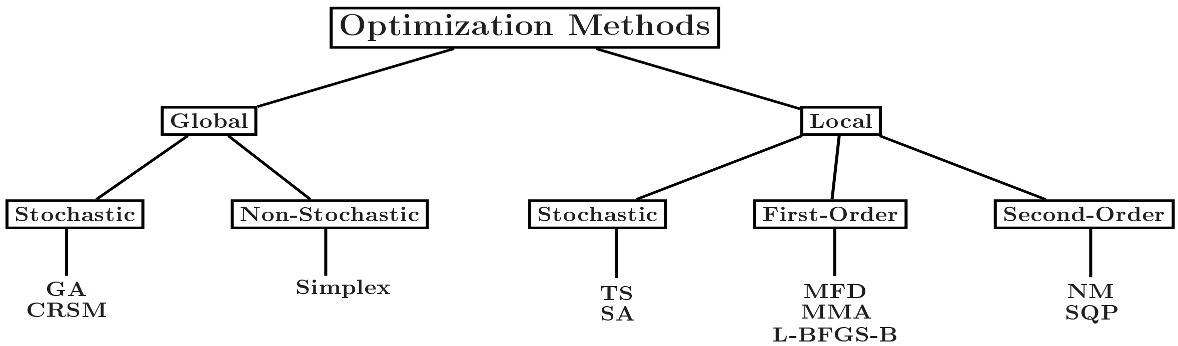

Figure 3.2: Various optimization methods considered in this study.

In the following subsections, a short review on the considered local and global optimization algorithms is presented.

3.2.1 Local Optimization Methods

The local methods converge to whatever local minimum is closest to the starting point during of the optimization. As a result, the global structure of an objective function is unknown to a local optimization method. Fig. 3.2 presents that local optimization methods are either gradient- or non-gradient based.

The local gradient-based methods follow this simple concept that they begin in each iteration of k from a start point ϑ_k and find the search direction d_k. Then they perform a one-dimensional line search by Eq. (3.1) considering a moving limit factor α to produce the new optimum variable ϑ_{k+1} by

$$\vartheta_{k+1} = \vartheta_k + \alpha \; d_k. \tag{3.1}$$

This process continues until some prespecified termination criteria are fulfilled.

Local gradient-based optimization methods use gradients of objective function and constraints. These gradients can be calculated either analytically, when the objective function is analytically available, or numerically, e.g., by finite difference method. Local optimization methods employ different ways to find the search direction and to control the move limits:

- **MFD — Method of Feasible Directions:** The basic steps in Method of Feasible Directions involve solving a linear or nonlinear programming subproblem to find the search direction and then finding the move limit along this direction by performing a constrained one-dimensional search [Vanderplaats 84]. The step size α is chosen so that the new design is feasible and has smaller cost function. They improve the design at each iteration, so that an acceptable solution may be achieved in early steps. MFD involves only first-order derivatives of objective and constraint functions.

- **MMA — Method of Moving Asymptotes:** The Method of Moving Asymptotes generates and solves in each step of the iterative process during the optimization, a strictly convex approximating subproblem. The generation of these subproblems is controlled by so called moving asymptotes, which may both stabilize and speed up the convergence of the general process [Svanberg 86]. In each iteration, the current point ϑ_k is given. Then an approximating explicit subproblem is generated. In this subproblem, the exact objective function is replaced by approximating convex function. This approximation is based mainly on gradient information at the current iteration point, but also implicitly on information from previous iteration points. The subproblem is solved and the unique optimal solution becomes the next iteration point. Then a new subproblem is generated, etc.

- **L-BFGS-B — Limited memory Broyden-Fletcher-Goldfarb-Shanno algorithm for Bound constrained optimization:** The Limited memory BFGS algorithm for Bound constrained optimization is that at the beginning of each iteration, the current iterate ϑ_k, the function value, the gradient of objective function, and a positive definite limited memory approximation of Hessian matrix are given. This allows to form a quadratic model. The algorithm approximately minimizes this quadratic model subject to the bound constrains [Byrd 95]. This is done by firstly using the gradient projection method to find a set of active bounds, followed by minimization of the quadratic model treating those bounds as equality constraints. After computing the Cauchy point, it finds a search direction d_k by either direct primal method or dual method. Then it performs a line search along d_k, subject to the bounds on design variables, to compute a moving length α_k, and calculate ϑ_{k+1} by Eq. (3.1). If the termination criteria have not satisfied, then the Hessian matrix will be updated and this process will be repeated.

- **NM — Newton's Method:** Newton Method is based on approximating the objective function locally by a quadratic model and then minimizing that function approximately. The quadratic model of the objective function at a design point ϑ_k along d_k is given. The minimum of this quadratic model is achieved when d_k is the minimum of the quadratic function [Dennis 83]. Alternatively, such a search direction d_k satisfies the linear system of n equations, known as the Newton equation. When the Hessian matrix is not positive-definite, the search direction may not exist or may not be a descent direction. Approximation strategies to produce a related positive-definite Hessian matrix or alternative search directions become necessary. Far away from an optimum solution, the quadratic approximation of the objective function may be poor, and the Newton direction must be adjusted. A line search for example can scale the search direction when it exists, ensuring sufficient decrease and guaranteeing uniform progress toward a solution.

- **SQP — Sequential Quadratic Programming:** The Sequential Quadratic Programming finds a step away from the current point by minimizing a quadratic model of the problem. This method is used to solve n-dimensional, nonlinear, constrained optimization problems by successive linearization of nonlinear functions [Spellucci 04]. The objective function and the constraints are linearized at the starting point in the design space using first order Taylor series approximation. The solution to this linear problem is obtained using standard linear programming techniques. The problem is then re-linearized at the approximate solution. This process is repeated until the termination criteria are satisfied.

- **SA — Simulated Annealing:** Simulated Annealing is based on the manner in which liquids freeze or metals recrystallize in the process of annealing [Kirkpatrick 83]. In an annealing process a melt, initially at high temperature and disordered, is slowly cooled so that the system at any time is approximately in thermodynamic equilibrium. As cooling proceeds, the system becomes more ordered and approaches a frozen ground state. Hence the process can be thought of as an adiabatic approach to the lowest energy state. If the initial temperature of the system is too low or cooling is done insufficiently slowly, the system may become quenched forming defects or freezing out in metastable states (i.e. trapped in a local minimum energy state). This method tries random steps; but in a long, narrow valley, almost all random steps are uphill, some additional finesse is therefore required. While the optimality of the final point cannot be guaranteed, the method is able to proceed toward better minima even in the presence of many local minima.

- **TS — Tabu Search:** Tabu Search was originally developed by Glover and has been successfully applied to a variety of combinatorial optimization problems [Glover 89]. However, very few works deal with its application on the global minimization of functions depending on continuous variables. A new algorithm called enhanced continuous tabu search by R. Chelouah and P. Siarry [Chelouah 00] was proposed for the optimization of multi-minima functions. It results from an adaptation of combinatorial tabu search which aimed to follow, as close as possible, Glover's basic approach. In order to cover a wide domain of possible solutions, this algorithm first performs the diversification: it locates the most promising areas by fitting the size of the neighborhood structure to the objective function and its definition domain. When the most promising areas are located, the algorithm continues the search by intensification within one promising area of the solution space to find the optimum design.

3.2.2 Global Optimization Methods

Most of the available optimization algorithms focus on certain types of optimization tasks. Some algorithms are well suited for unconstrained optimization, whereas others are designed for constrained problems. Some methods require the objective function and the constraints to be linear functions of the design variables, others can handle quadratic or generally nonlinear objective functions and constraints. One can also distinguish between local optimization algorithms, which might get trapped in a local extremum, and global techniques, which always find the global extremum.

As it is depicted in Fig. 3.2, three optimization methods are considered for the global optimization study, namely, Genetic Algorithms (GA), Controlled Random Search Method (CRSM) and a modified version of Simplex method. A general description of these methods are presented in the following as:

- **GA — Genetic Algorithms:** A very compact description of the basic concepts of a genetic algorithms method can be found in [Charbonneau 03]. The following is an even more condensed excerpt from that reference. Suppose there is a set (or vector) of design parameters $\boldsymbol{\vartheta}$ and a model that relates the parameters $\boldsymbol{\vartheta}$ to some measure of quality or fitness $\mathcal{F}(\boldsymbol{\vartheta})$ for a particular design, i.e., for a particular vector of design variables $\boldsymbol{\vartheta}$. Now the optimization algorithm has to find the one set of variables that maximizes the fitness function. A basic GA works then as follows: randomly initialize population and evaluate fitness of its members, breed selected members of current population to produce offspring population (selection based on fitness), replace current population by offspring population, evaluate fitness of new population members and repeat until the fittest member of the current population is deemed fit enough.

- **CRSM — Controlled Random Search Method:** A random search method which use uniform-random-direction-linear-search local minimization algorithm proposed by Timo Jarvi in his Ph.D. thesis [Jarvi 73]. Tibor Csendes [Csendes 95] presented a modified version of random search method, namely, Controlled Random Search Method. The framework for this modified random search method is that the best local minimum found is with high probability the global minimum [Ali 97]. Indeed, this method performs a random search on the entire of search space and presents the best founded minimum as the global minimum.

- **Simplex:** The Simplex algorithm by Nelder and Mead, see [Nelder 65], requires only function values but no derivatives. It should not be confused with the simplex method of linear programming [Dantzig 63]. A simplex is a geometrical figure that consists of $n+1$ points (also called vertices) in n dimensions and all the line segments and polygonal faces that connect the vertices. Thus, a simplex is a triangle in two dimensions, a tetrahedron in three dimensions, and a general polyhedron in more than three dimensions. A simplex is called nondegenerate if it encloses a finite inner n-dimensional volume. The initial simplex is defined by $n+1$ vertices each of which is a vector of design variables $\boldsymbol{\vartheta}$ of length n. If any of the vertices is considered the origin, then other n vertices can be considered vector directions that span the n-dimensional vector space. Therefore, an initial simplex can be formed by first defining just one initial vertex ϑ_0 (start vector) and by then determining the other n vertices of the simplex ϑ_j ($j = 1, 2, \ldots, n$). The algorithm computes the objective function value $\mathcal{F}(\vartheta_i)$ at all vertices ϑ_i ($i = 1, 2, \ldots, n$). Then, the vertex with the worst (i.e., largest in case of function minimization) objective function is replaced by a new one that results from reflection at the mean value of the remaining n vertices. Furthermore, expansion and contraction can occur (depending on the success of the reflection) to adapt the shape of the simplex in order to maintain its nondegeneracy. These steps are repeated iteratively until the termination criterion is met. The iterations are stopped if the standard deviation falls below this predefined value. In this dissertation, a modified version of simplex methods is used. To make simplex method suitable for global optimization, it is combined with the method of Design of Experiments (DOE). In this case, DOE makes a global approximation from the objective function.

3.3 Approximation Methods

Function approximation methods are often applied independently of the type of optimization algorithms. Many optimization algorithms use approximation concepts to allow a simpler representation of the actual objective function. An excellent survey about approximation concepts has been provided by van Houten [van Houten 98]. Fig. 3.3 shows the considered approximation methods for this study. In general, we distinguish local, global and mid-range approximation. These methods are shortly explained in the following subsections.

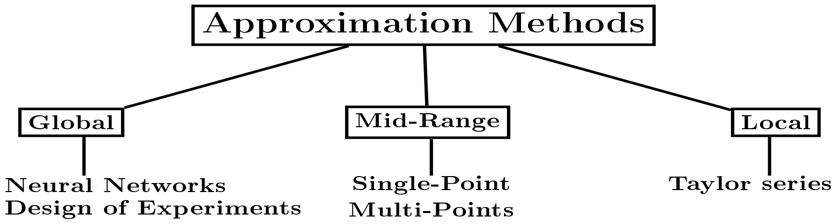

Figure 3.3: Various approximation methods considered in this study.

3.3.1 Local Approximation Methods

The term local refers to this fact that only information about an objective function from the neighborhood of the current approximation is used in updating the approximation. Therefore, these approximations are valid only in a small subregion of the total search region. In their simplest form, linear approximations are used. Local approximation is based on a reference design and, mostly, a Taylor series approximation. First order approximation is using gradient approximation, second order requires the Hessian too.

3.3.2 Global Approximation Methods

Global methods are used to find an approximation of the objective function for the entire design space or, at least, for a large region of it. This requires a relatively large number of points to fit the approximate function to the data. Typical members of global approximation methods are neural networks [Papadrakakis 99] and design of experiments [Montgomery 01].

- **NN — Neural Networks:** The NN method is more suitable for the applications in which is no way to describe the problem with a function. A trained network presents a rapid mapping of given input into the desired output quantities, thereby enhancing the efficiency of the redesign process. The NN training comprises the following tasks. At first select the proper training set, then find the suitable network architecture and determine the appropriate values of characteristic parameters such as the learning rate and momentum term [Papadrakakis 99].

- **DOE — Design of Experiments:** DOE method is a systematic approach for the investigation of a system or process. A series of structured tests are designed in which planned changes are made to the input variables of a process or system. The effects of these changes on a predefined output are then assessed [Montgomery 01]. The construction of response surface models and the design of experiments is an iterative process and consists of several steps. The first step is to select a function approximation model (linear, quadratic etc.) for the objective function. Next, data points are selected to run numerical analysis. After the function models have been fitted to the response data, the functions must be checked for their validity to represent the real behavior of the response functions. Decisions on how to proceed to the next step must be made by the designer and influence the success of the optimization problem solution.

3.3.3 Mid-Range Approximation Methods

Methods that combine most of the strengths of local and global methods are known as mid-range approximation methods [Kessels 01]. They are classified as single-point or multi-points. The corresponding approximate response functions are simple and often explicit in terms of the design variables. Mid-range function approximations of objective function and constraints are valid in a region larger than local methods but smaller than global methods. First a model function has to be selected. Next the set of design points to be used in the fitting of the model are either newly generated or used from previous cycles. Finally the unknown function parameters are calculated. To restrict the region of validity, usually bounds to the design variables are imposed, so-called move limits [Etman 97, Keulen 97].

In local methods, all information from previous cycles is discarded. When data from earlier cycles is stored and used in later steps, more accurate approximations and larger search regions can be applied. Such methods are termed mid-range single point path methods, since a single new point is added in each cycle. The multi-points approximation method replaces an optimization problem by a sequence of approximate ones [van Houten 98]. In a multi-points path method, in each cycle one or more new design points are generated within the move limits to base the approximations on, but data from previous steps can also be used.

In this dissertation, a mid-range multi-points approximation approach is used. A linear approximation of the objective function within the move limit area is considered for the optimization process. The minimum of the approximated objective function is searched by MFD.

Chapter 4

Optimization Procedure

In this chapter, the optimization procedure constituting the numerical structural acoustic optimization programs is described. Sections 4.1, 4.2 and 4.3 provide some information on issues that are common to all of optimization algorithms employed. Sec. 4.1 presents the general framework of an optimization procedure. Then, Sec. 4.2 introduces the formulation of the optimization problem and some necessary initializations for the beginning of an optimization process. The convergence criteria is presented in Sec. 4.3. The last two sections of this chapter focus on aspects of the optimization procedure that are unique to each of optimization algorithms as well as the control parameter setting and the calculation of objective function.

4.1 Optimization Procedure in General

Figure 4.1 gives an overview of the general optimization procedure. Certain components of this flowchart contain subprocedures, which are described in more detail below. The first step is to create an initial FE model of the structure to be optimized. The initial FE model of the structures will be investigated in the present study in Chap. 5.

The second step is to perform an FE analysis of the initial FE model created in the first step. This is accomplished by using the commercial FE software ANSYS [ANSYS]. A combination of a numerical modal analysis and a subsequent mode-based steady-state dynamic analysis provides the nodal rms surface velocity vectors $\upsilon_{rms\imath}(\omega)$ (see Sec. 2.2).

In third step, the initial design is evaluated, i.e., the objective function and the constraints are computed and saved to files to allow a continuous comparison between the initial design and the modified designs during the optimization. The numerous subprocedures of this step are explained in the following subsections.

In fourth step, the actual optimization procedure is started. This involves the execution of several Unix shell scripts and mixed C, C++ and Fortran programs. This step is described in a separate section below, namely, Sec. 4.1.2. The fourth and fifth steps invoke the actual numerical approximation and optimization algorithm, which iteratively generates new design variable values based on the previous optimization history and success. The optimization and approximation algorithms are described in sections 3.2 and 3.3. Individual aspects of this step are treated in Sec. 4.5.

Steps six through eight constitute the evaluation of the modified design. Step six transforms the new design variable values produced in steps fourth and five into a new, modified FE model of the structure. The FE analysis of the modified design in step six is carried out

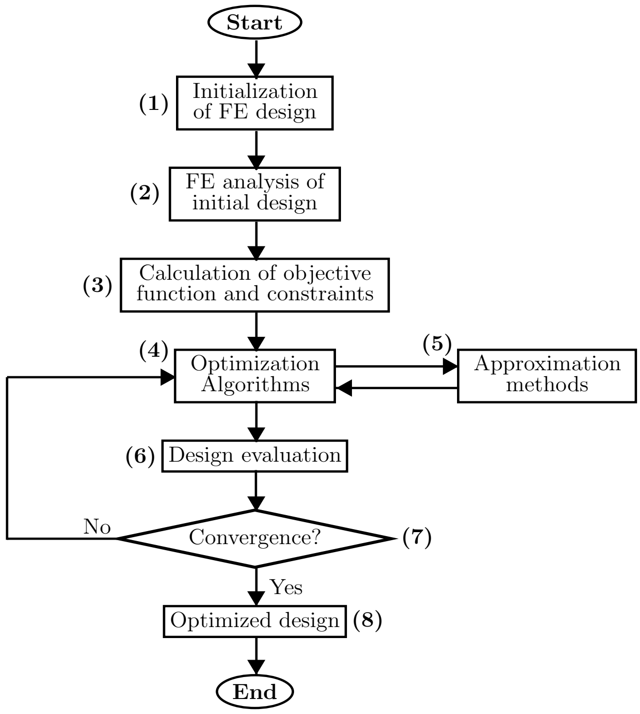

Figure 4.1: General flowchart for the structural acoustic optimization.

in the same way as in step two above. Step six provides the new objective function value and the constraint values for the modified design as in step three described above.

The convergence check in step seven is similar for the optimization algorithms and is described in Sec. 4.3. If the convergence criterion is not yet met, the procedure branches back to step (4) to generate a new vector of design variables.

However, if the convergence criterion is met, the optimization result is evaluated and recorded in step (8). The final product of the optimization process is an FE model of the optimized design.

This optimization procedure is designed and organized such that it can run automatically without any manual intervention for hours, days, or even weeks until the stop criterion is met. It is, however, possible to influence certain process parameters (the maximum number of function evaluations, the amount of information output to the screen or log file, etc.) while the optimization is running, because they are read from a control parameter file, which can be edited.

It is not trivial to organize this process in such a way that the right information is available to the various separate Fortran programs and Unix shell scripts at the right time at the right place (various directories, subdirectories, and files, sometimes even on different computers). The whole procedure is rather complex since an Unix shell script invoke other Unix shell scripts that start Fortran and C programs that start a number of other Fortran and C++ programs that in turn invoke Unix shell scripts that again start other Fortran programs. Some quantities are “static”, which means they need to be calculated or determined only once, i.e., prior to the first iteration at the start of the procedure, because they do not change from iteration to iteration. Examples include the number of nodes and elements in the FE model. They are written to files from which they can be simply read again during subsequent iterations. Other quantities are “dynamic”, i.e., they vary from iteration to iteration and are therefore computed and determined anew at each iteration. Examples for "dynamic" quantities are the nodal coordinates, the structural mass, and the results of the FE analysis.

4.1.1 Calculation of Objective Objective Function and Constraints

The objective function is calculated and the constraints are evaluated in steps (3), (4) and (6) of Fig. 4.1 by a program module.

In the first step of this module, parameters that control the optimization procedure or that are necessary to define the size of dynamic variable arrays in the various Fortran programs are read from the control parameter file. Then the "dynamic" results of the FE analysis are read from the binary result file, i.e., quantities that change from iteration to iteration such as the nodal coordinates, the nodal rms surface velocity vectors $v_{rms\imath}$ (see Chap. 2), the surface area, or the structure's natural frequencies.

In the next step, the nodal normal rms surface velocities $v_{rms\imath}(\omega)$ are computed according to Eq. (2.7). Furthermore, the RMLS is computed according to Eq. (2.9), where the lower and upper bounds of the frequency range under consideration, ω_{min} and ω_{max}, are read from the control parameter file in step (1). Now the objective function and bound constraints are available.

4.1.2 Start of Optimization Procedure

The optimization process starts in step (4) of the flowchart shown in Fig. 4.1. All information and intermediate results produced during optimization are written to the specific log files. The iteration number is initialized to zero and written to another file where it can be read from or, after an increase, written to again. After that, a Unix shell script invokes the computation of the objective function and the evaluation of the constraints in step, and then starts the actual optimization algorithm, i.e., either local, mid-range approximation and global methods, depending on the respective choice of user. When the user decide to employ the approximation methods during the optimization procedure and specifies the type of approximation method, then the optimization algorithm connects to the selected approximation program. A Unix shell script removes all old job files that might still exist in the current directories and subdirectories from a previous FE analysis and optimization run.

4.1.3 Evaluation of Modified Design

The new design variable values, which are generated by the optimization algorithm at each iteration in step (4) and(5) of Fig. 4.1, are used to create a new FE model of the structure.

Upon completion of the FE analysis, the new objective function value for the modified design is evaluated.

In the final step, the new objective function value is returned to the optimization algorithm, which starts a new iteration by generating new design variable values if the stop criterion is not yet met.

4.2 Formulation of the Optimization Process

Optimization is defined as the minimization or maximization of an objective function subject to constraints on its variables [Nocedal 99, Marburg 02a].

Herein, the optimization problem is defined as follows

$$F(\boldsymbol{\vartheta}) \ = RMSL(\boldsymbol{\vartheta}) \quad \longrightarrow \quad \min \tag{4.1}$$

while the design variables ϑ_i (which are assembled in $\boldsymbol{\vartheta}$) remain in a prescribed interval of lower and upper modification values as

$$-h_{\max} \ \leq \ \vartheta_i \ \leq \ h_{\max} \qquad \text{with} \quad h_{\max} = 10mm\,. \tag{4.2}$$

Equation (4.2) defines the design space just as a nine-dimensional cube since all parameters are allowed to take values within the same fixed interval and all parameters are independent of each other. There are no additional equality and inequality constraints.

As mentioned before, the design variables, ϑ_i ($i = 1, \ 2, \ldots, \ 9$), are the positions of specific points, in other words, the normal geometry modifications at these movable points. If the shape of the surface is varied by means of a spline function, then the positions of the spline points are the design variables. It is assumed that the thickness of the plate remains constant. For illustration, see Ref. [Marburg 02b].

To have a common basis for the comparison of optimization methods, 1000 sets of initial design sets in which each set has nine initial design variables, are prepared. The members of these initial designs are chosen uniformly from all parts of the search space. A uniform random number generator introduced in ref. [Press 02] produces the possible candidates with a uniform distribution on the entire search space. In this case, the search space is the allowable range of design variables.

The random numbers are normalized and located uniformly between 0 to 1. To show the uniformity of the initial set of design variables, the search space is divided into 100 equal segments (NS= 100). Then, each segment has a length of 0.01. The distribution possibility of random numbers (H in %) on each segment is calculated by the total number of existed random points in each segment divided by the total number of produced random points,

$$H(\%) = N/n_R \cdot 100. \tag{4.3}$$

To show the uniformity of the data distribution on the search space, a data distribution uniformity factor called $\overline{H}$ is defined as

$$\overline{H}(\%) = \frac{\sum_{i=1}^{100} H_i}{NS}. \tag{4.4}$$

Distribution probability shows how many random points are located in each segment of the search space. The mean value of the probability distribution for a good uniform random number set should be one. That means in every segment of the search domain between 0 to 1, there are the same number of random numbers. The uniform random set which is considered for this study has 10 random numbers in every search segments.

Fig. 4.2 confirms that the mean value for the distribution probability of the produced set of initial designs with 1000 members is one. Therefore, it is confirmed that the initial set of random design variables for the optimization processes are selected uniformly from the entire of design space.

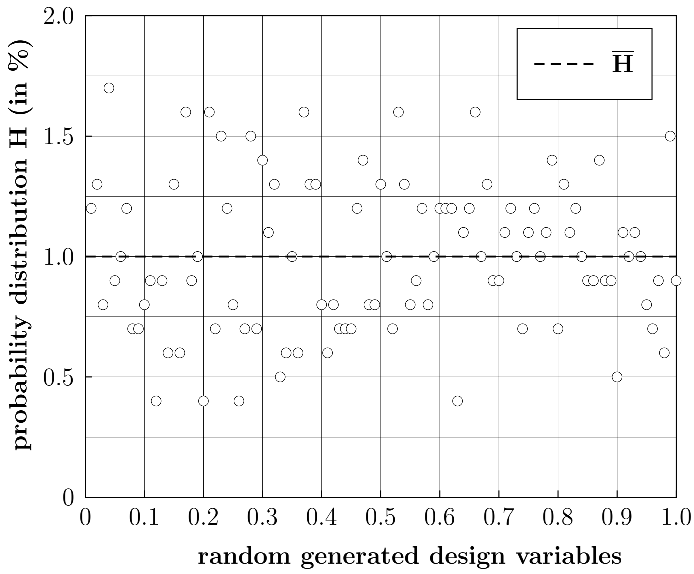

Figure 4.2: Uniform distribution of 1000 random design variables on the normalized search space.

4.3 Convergence Criteria

The main convergence criterion used in this study for all of methods, is the maximum number of function evaluations. This termination value must be specified by the user in the initial control parameters setting file. When the total number of function evaluations reaches to the prespecified maximum number of function evaluations, then the optimization procedure becomes terminated. At this stage, the best design variable vector found is returned as the optimum set of design variables.

Sometimes it happens that the final design is not feasible in the strict, mathematical sense, i.e., one or some constraints may be slightly violated. In this case, the design variables those violated the constraints are replaced with the allowable boundary values in the respective range. This allowable values are nothing else than the upper or lower bounds on the design variables. Then the new objective function is being evaluated and reported. Nonetheless, from the engineering point of view it does not matter if the geometry modification at any location is a little bit, i.e., 10^{-5} higher or lower than the respective limit, since this order of magnitude is hard to achieve in the manufacturing process anyway and therefore irrelevant.

Often, some optimization methods use the last hundreds, sometimes even thousands of function evaluations just to avoid even the slightest constraint violation while the objective function is not significantly improved or even not improved at all. Therefore, it seems to be sensible to define a tolerable constraint violation of 0.01% for all of optimization methods.

The main termination criterion used in this thesis is the maximum number of function evaluations. This holds for all methods.

4.4 Control Parameter Setting

There are several parameters that control the behavior of optimization and approximation algorithms. Some of them have an extreme influence on the convergence rate and efficiency of the algorithms. However, the setting of these parameters is very problem dependent, which means that general recommendations cannot be made in advance. Rather, good parameter values must be found in a trial and error manner. Since each of the optimization runs took a lots of time, it is obvious that an exhaustive parameter optimization could not be performed prior to the actual optimization run, particularly since the best control parameter set for one problem can have disastrous effects on the efficiency of solving another problem. Hence, the default values for control parameters of the optimization methods are basically left unchanged except for some parameters which are explained in Appendix A.

4.5 Calculation of Objective Function

The previous section described features and procedures that are common to all of optimization algorithms used in this study. This section and Sec. 4.3 explain issues that are unique to the exact optimization algorithms on the one hand and to the approximate optimization algorithm on the other hand.

The term of "exact" refers to this fact that during the optimization procedure, only the exact value of objective function is used.

A detailed description of the optimization and approximation algorithms is beyond the information provided in chapter (3) is not considered necessary. Instead, the focus of this section is on the calculation of the objective function and the evaluation of the constraints, on the convergence criterion, and on feasible results and tolerable constraint violations.

The approximate optimization methods are those using the approximation concept by nature, i.e., the approximated gradients or approximated Hessian Matrix including of approximated second derivatives like L-BFGS-B, MMA and MMP or the methods which have this option to consider the approximated values of the derivatives like NM, SQP and MFD.

All gradient information are calculated by the finite difference approximation. The Hessian matrix for Newton's method is calculated by the finite difference approximation and it is a priori assumed to be symmetric. For SQP, a slightly modified version of the Pantoja-Mayne update for the Hessian of the Lagrangian, variable dual scaling and an improved Armijo-type stepsize algorithm are used [Spellucci 98].

Although the NN and DOE are basically considered as the approximation methods, but here they are combined with some optimization methods to be used for the optimizations purposes.

In HDOE method, a full factorial version of DOE method is considered to make a full linear approximation of the objective function by method of design of experiments (DOE). This type of approximation is easy to use and always applicable. Linear approximation of an objective function with nine design variables need 10 points to build its approximated objective function in each optimization iteration. These points should be consider uniformly on the entire of design space. After building the approximated objective function, for finding the minimum of linear approximate function, the simplex method is used. In fact, HDOE algorithm is a hybrid method including of method of Design of Experiments as the function approximation tool and the Simplex Method as the optimizer tool.

As there is no way to define an analytical mathematical formulation for the objective function in this thesis, then numerical calculation of objective function is necessary. The FE analysis of the problem is very time consuming. In fact, the main part of each optimization iteration is being consumed by the FE analysis for calculation of objective function. Therefore, finding an alternative way to reduce the computation time is useful.

There are several methods available to calculate the objective function. Some fast FE methods are still under developments by the researchers and the performance of these methods should be investigated more. Neural networks (NN) is another methods that trains a set of neurons to work as a replacement for the main objective function. For this purpose, a set of training members including the main objective function's values in several design points. Then the neural network is being trained to simulate the main objective function virtually. The time of objective function calculation by NN is very shorter than the time which is required to calculate the objective function numerically by FE methods.

In this thesis a NN is used to be trained for the calculation of objective function. The objective function values produced by NN are used for the optimization process by SA method. Indeed, HNN is a combination of method of Neural Networks as the function approximation toll and method of Simulated Annealing as the optimizer tool.

The considered neural network has five hidden neurons and uses the back propagation learning algorithm. Initial and final learning rates are 0.1 and 0.01. NN using an initial training set of 110 function samples. Training loop is repeated for 100 times. The optimization iterations is continued up to 500 times. However, this number of function evaluations is no problem as it takes actually a very short time. A back propagation learning algorithm with five hidden neurons is used. Initial and final learning rates are 0.1 and 0.01 in order. The NN uses an initial training set of 110 function values. Each function evaluation consumes around one minute CPU time on a SGI-Altix 3700 cluster. Then, an initial 110 minutes computation time must be invested for the calculation of training set. There are a lot of possibilities to consider different combinations of different larger or smaller training sets, different number of training loops, the number of neurons and layers and input-output learning rates. Choosing the best parameters for a good neural networks needs itself a separate study and even with try and error approach. Sa method is employed as the optimization tool. It uses the calculated approximate function values by NN method for the minimization process. In this thesis, the optimization process is specially arranged to begin from the same initial design like other previously investigated methods. It is mainly done to prepare a same base for the comparison study.

Tuning of suitable initial parameters for optimization methods need a try and error approach and is beyond of scope of this study. Therefore, the basic and previously recommended initial settings for the SA [Corana 97], TS [Chelouah 00], CRSM [Csendes 95], MFD [Vanderplaats 84], L-BFGS-B [Byrd 95], SQP [Spellucci 04], NM [Dennis 83], MMA [Svanberg 86], MMP [van Houten 98], HNN [Corana 97, Papadrakakis 99] and HDOE [Montgomery 01, Nelder 65] are used to avoid the excessive effort for finding a well tuned set of initial parameters. Although, it will never be a worthy effort, because the set of initial parameters are problem dependent and may not work well for other optimization applications.

In this thesis, the initial parameter setting for the GA is like what Charbonneau reported in his report [Charbonneau 03]. However several runs of GA with different initial populations and number of generations are experienced. For example in the first case, a population with 100 initial members with 5 total generations is considered. In another case, an initial population with 20 members but with 25 total generations is examined.

GA requires the computation of a so-called fitness function, which must be a positive definite quantity. The fitter an individual is, i.e., the higher its fitness value, the higher is its chance of being selected for reproduction in the next offspring generation.

4.5.1 Minimum Number of Objective Function Calculation

Table 4.1 shows the minimum number of function evaluations which is necessary to be performed in each optimization iteration. For an objective function with n design variables, a zero-order optimization method, e.g., SA, needs at least one function evaluation in each iteration while the gradient-based optimization methods, e.g., MFD, MMA, L-BFGS-B need to perform at least $n + 1$ function evaluations to calculate the gradients and the objective function.

Table 4.1: Minimum required number of function evaluations in each iteration for various combinations of optimization and approximation methods.

Method Optimization/Approximation	Function evaluations	Gradients evaluations	Hessian matrix evaluations	Total evaluations
SA/-	1	-	-	1
MFD/FDM	1	n	-	n+1
MMA/FDM	1	n	-	n+1
SQP/BFGS	1	n	-	n+1
L-BFGS-B/BFGS	1	n	-	n+1
NM/FDM	1	n	n(n+1)/2	(n+1)(n+2)/2
Simplex/DOE	variable	-	-	variable
SA/NN	variable	-	-	variable
GA/-	variable	-	-	variable
MMP/FDM	variable	variable	-	variable
CRSM/FDM	variable	variable	-	variable

Because there is no explicit objective function available, then the values of first and second derivatives of the objective function should be approximated by means of the finite difference method. Although the SQP method is a second-order method but in this dissertation a special version of this method is used. The BFGS approximation method is employed to approximate the values of the Hessian matrix's elements. In this case, the minimum required objective function evaluations for SQP method is $n + 1$. It is almost the same done for L-BFGS-B but a different line search algorithm is used.

When it is required to calculate the second derivatives of objective function numerically, the finite difference method is used to calculate the members of the Hessian matrix. In general, a full Hessian matrix must be calculated, then in this case, $n^2 + n + 1$ function evaluations must be performed in each iteration. If the objective function is positive definite and the optimization problem is convex, then it is possible to assume that the Hessian matrix for the current objective function is symmetric. In this case, it is enough to calculate only the lower triangular elements of the Hessian matrix. Then, it is only needed to calculate $(n + 1)(n + 2)/2$ objective function values in each iteration for a second-order optimization method. NM is a second-order method and table 4.1 shows the minimum required objective function evaluations for a positive definite and convex problem. Although this assumption is not true in general but it is simply done to save the computation time and to experience the effect of such assumption on the final results of this method.

The minimum required number of function evaluations for HDOE and HNN methods is variable. It is depended on the type of objective function approximation by these methods.

It is also not actually possible to indicate a minimum required number of objective function evaluations for GA, MMP and CRSM methods.

Chapter 5

Finite Element Model

In this chapter, the FE model investigated and optimized in this thesis is introduced. Section 5.1 provides some information on the FE model. Employing of bicubic splines for the reduction of design variables is discussed in Sec. 5.2. Finally, the approach which is used in this study for the frequency discretization is presented in Sec. 5.3.

5.1 The FE Model of Rectangular Plate

The structure to be optimized in this paper is a square plate made of steel [Fritze 03]. At least, the initial design is a plate. After modification, the plate changes into a shallow shell. The commercial finite element code Ansys is used. The geometry is defined by 25 points which are evenly distributed over a square of 1m edge length. These points are connected by lines which are actually created by Spline interpolation. Of course, using Splines is not necessary as long as we consider a flat plate. However, the optimization leads to a shallow shell for which the Spline interpolation becomes relevant. Lines are forming areas. Finally, the plate is composed of 16 areas. Each area is meshed by 5×5 quadrilateral, eight node Serendipity shell elements, i.e. the plate's mesh consists of 400 finite elements. In Ansys, the elements are called *shell93* [ANSYS]. The plate is simply supported. It is 1 mm thick. Fig. 5.1 depicts the model. Excitation is applied by local harmonic pressure loads which are applied as shown in Fig. 5.1. There are three uniform harmonic pressure excitations on the surface of plate. All of them act at the same amplitude and phase and are uniform over the frequency range of 0-100 Hz. The excitation pressures act at the locations where presumably all relevant mode shapes of the structure in the frequency range of interest are excited.

For the optimization process, it is assumed that the geometry defining points on the edges of the plate to be fixed. However, location of the remaining nine points may be varied into normal direction. These nine points are emphasized in the left subfigure of Fig. 5.1.

A density value of $\rho = 7850$ kg/m^3, an elastic modulus (Young's modulus) of $E = 2.1 \cdot 10^{11}$ N/m^2, and a Poisson's ratio of $\nu = 0.3$ are considered for the model. The damping is assumed to be independent of the frequency with a constant damping coefficient of 0.3%. Structures with a relatively small damping coefficient can be considered lightly damped so that the modal superposition technique can be applied with negligible error for the FE calculation of the nodal rms surface velocity vectors $\upsilon_{rms\imath}(\omega)$.

The support boundary conditions for the structure, are chosen to be so-called simple supports, which means that the edges of the structure do not have any translational DOFs (they cannot move up and down or sideways) but they do have rotational DOFs (they are

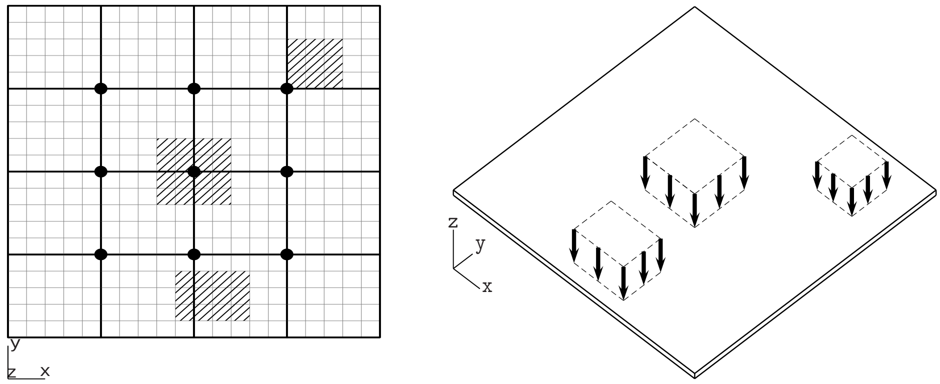

Figure 5.1: (I). Initial FE model with 20×20 movable elements, three excitation (hatched) areas and 9 geometric points. (II). The excitations areas on the plate.

free to rotate about the particular edge under consideration).

The excitation pressure are three harmonically varying surface pressures. However, the amplitude of the pressure loads are not relevant because the mean squared rms normal velocity $\overline{\upsilon^2_{\perp rms}(\omega)}$ is divided by the square of the rms excitation force $F^2_{rms}(\omega)$ when the mean squared transmission admittance $h^2_t(\omega)$ is calculated in Eq. (2.3), thus negating the influence of the excitation force's amplitude. The excitation pressures always act perpendicularly to the sound radiating surface at some areas on the structure.

The Block Lanczos method is used for the modal analysis of the model. Also, the super positions method is used for the harmonic analysis of the model. A maximum mode frequency of 150 Hz and a maximum modes number of 100 are considered. The density of air is considered as 1.3 kg/m^3.

5.2 Employing of Bicubic Splines to Reduce the Number of Design Variables

Even for a simple structure like the rectangular plate depicted in Fig. 5.1, the number of design variables, i.e., the number of surface nodes at which the local geometry can be changed, is quite high. The optimization algorithm has to check and control all of these design variables, which takes a lot of computation time. Hence, it is desirable to reduce the number of design variables in order to save CPU time.

The number of design variables can be quite high depending on the structure's FE model and its discretization. Therefore, a spline function is employed to reduce the number of design variables in this chapter.

The surface key points, the position of which can be varied along the z coordinate and optimized by the optimization procedure, are marked in Fig. 5.2. The nodes at the edges of the plate are not part of the modification domain. The number of movable surface nodes totals 1521. If no spline functions are used to reduce the number of design variables, then the optimization procedure directly varies these node positions, which leads to 1521 design variables. If spline functions are used, this number is reduced to 9 in this study.

The surface of the structure is modeled by spline functions. First, a geometry distribution is calculated by means of a spline surface. Then the FE nodes of the structure are moved

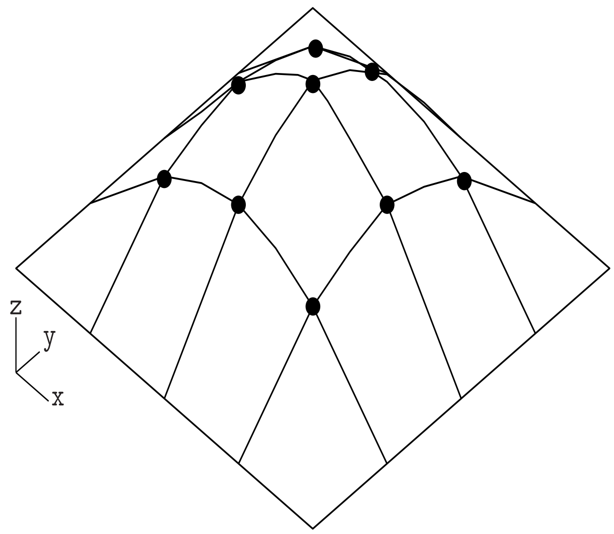

Figure 5.2: Modification of 3×3 movable design point positions on the surface of rectangular plate by means of a Bicubic spline surface.

such that the geometry of the structure corresponds to this calculated geometry distribution. This leads to a considerable CPU time saving compared to the same optimization without using splines.

The technique presented in this chapter was initially inspired by a paper by Braibant and Fleury [Braibant 84]. Marburg [Marburg 02b], Fritze et al. [Fritze 03] and Bös [Bös 03b, Bös 04] published several papers using this technique. For further details the reader is referred to the references just mentioned as well as to the literature on spline functions, e.g., the books [de Boor 78, Engeln-Müllges 96].

Three different spline formulations were presented in [Bös 03b], namely, a bicubic spline surface, a Hermite spline surface, and a tensor product Bézier surface consisting of Bernstein polynomials. Numerical experiments showed [Bös 03b] that the optimization results are very similar for all three spline functions and that none of them can be considered significantly superior to the other two [Bös 04]. Only the Hermite spline surface seemed to exhibit slight advantages with respect to the number of iterations needed to reach convergence as well as to the objective function improvement.

Marburg [Marburg 02b] and Fritze et al. [Fritze 03] showed that geometry modification of the shells and thin plates can reduce the radiated sound power level from them. In current thesis, the modification variables $\vartheta_1, .., \vartheta_9$ which are defined by the the modification key-points on the surface of the plate, build new geometries for the model. This new modified geometry reduces the value of RMSL for the new structure.

To calculate the spline surface, the first and mixed derivatives at the design key points are determined from the given nodal coordinates by means of finite difference method. The bicubic spline surface is generated in such a way that it is C2 continuous, which means that not only the nodal coordinates and the gradients (first derivatives) but also the curvatures (second derivatives) of the surface match at the key points. However, no derivatives but only the z coordinates of the key points must be supplied by the user.

Although in a study by Bös [Bös 04], it was shown that the bicubic spline function reproduces all key points exactly but tends to "overshoot" between the key points. Nevertheless, the surface defined by the key points is smooth and well approximated.

5.3 Frequency Discretization

One of the most challenges in every finite analysis is making a suitable FE meshing network. As coarse FE meshes produce the numerical error and fine FE meshes need more time for the computations.

In numerical analysis, computational physics, and simulation, discretization error is error resulting from the fact that a function of a continuous variable is represented in the computer by a finite number of evaluations, for example, on a lattice. Discretization error can usually be reduced by using a more finely spaced lattice, with an increased computational cost.

Discretization error should not be confused with round-off error arising from floating point arithmetic. Discretization error would occur even if it was possible to use exact arithmetic.

Discretization error is the principal source of error in methods of finite differences and the pseudo-spectral method of computational physics.

A too coarse discretization can cause numerical errors in acoustical FE analyses as discussed by Ihlenburg in his book and papers [Ihlenburg 95, Ihlenburg 98, Ihlenburg 03]. He observed that the classical "rule of thumb" of 6 to 10 linear finite elements per wavelength, which is usually recommended in practice, results in quite large numerical errors. If a small numerical error is desired or required, a drastically refined mesh must be used. This is due to the so-called numerical pollution effect, which occurs in addition to the FE approximation error and dominates the total error at higher frequencies. The numerical pollution can be interpreted as a numerical dispersion, i.e., due to these numerical errors the speed of sound c seems to become frequency dependent even in media in which this is physically not the case, e.g., in air where $c \neq c(f)$.

In his paper, Ihlenburg [Ihlenburg 03] provided resolution rules, which, if followed, result in an admissible error for the FE solution of the dynamic Kirchhoff plate equation. A coarse discretization significantly reduces the computation time for every single FE analysis. Since an optimization run requires hundreds, even thousands of iterations, each second of CPU time saved per iteration shows large effects.

A study by Marburg [Marburg 02d] showed that generally for the discretization in low-frequency ranges, it is six elements per wavelength enough.

The plate was discretized with different number of FE coarse and fine meshes. The result was that a meshing network including 20×20 quadratic elements are enough for this study. Then, the length is discretized with 20 elements, the width with 20 elements, and the thickness with only one layer of elements, totaling 400 elements.

In current dissertation, the different cases for frequency discretization were experienced. The results showed that for the frequency range of 0-100 Hz, it is better to consider three frequency steps for dynamic (modal and harmonic) analysis of the FE model. The reason is to save the information about the existed resonances in this frequency range. Moreover, it makes possible to avoid from the time consuming computations for doing the harmonic analysis in the case when a very fine frequency discretization is considered.

Fig. 5.3 shows three frequency discretization areas considered for the harmonic analysis. These frequency steps are $\Delta f_1 = 0.1$ Hz, $\Delta f_2 = 2.5$ Hz, and $\Delta f_3 = 0.5$ Hz for the frequency ranges of 0-40 Hz, 40-60 Hz and 60-100 Hz, respectively.

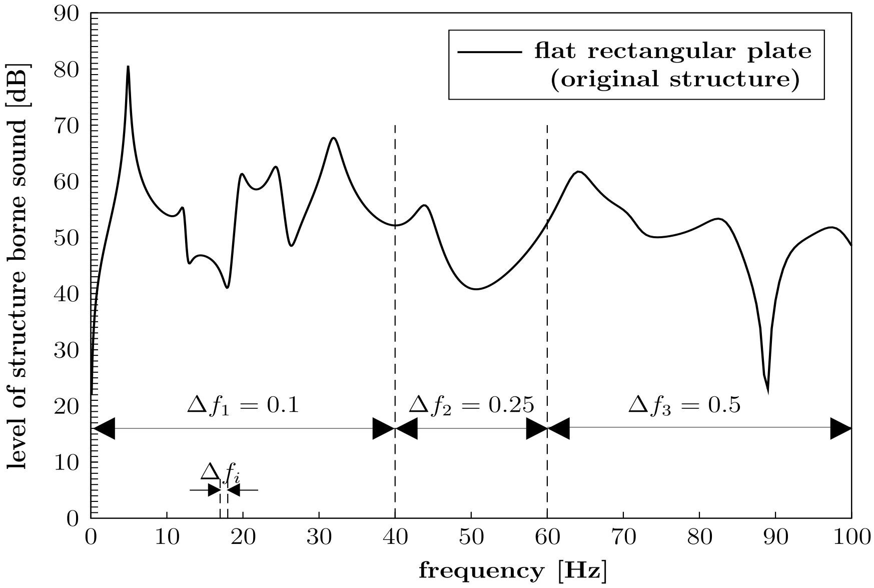

Figure 5.3: Discretization of the frequency range for the harmonic analysis of the FE model.

Chapter 6

Optimization Results

This chapter presents the optimization results. The FE analysis results of original plate are given in Sec. 6.1. It should be mentioned that in this chapter, two study approaches are considered. At first, one initial design is considered as an example for study of several optimization methods. The optimization results from this approach are presented in the section 6.2. Section 6.3 describes the optimization results for the GA method. Furthermore, the summary of optimization results for the case when a set of 1000 initial designs are considered, is presented in Sec. 6.4. The robustness level of optimization methods is also reported in this section. Finally, in Sec. 6.5, some issues about the parallelizing of methods are discussed.

6.1 Original and Initial Designs for Rectangular Plate

This section shows the FE analysis result for the original rectangular plate model prior to optimization. This information is intended to provide a means of assessing the effectiveness of the optimization results by comparing them with the properties of the initial structures.

The root mean square of the radiated sound power level RMSL of the original flat rectangular plate in the frequency range of interest 0-100 Hz is 45.31 dB, where the maximum radiated sound level of 80.56 dB can be found in the spectrum at the fundamental frequency 4.9 Hz. The LS spectrum of the original structure is shown as a solid line in various plots such as, e.g., Fig. 6.2.

Table 6.1 summarizes the properties of the original flat plate. All of the quantities listed in this table can basically serve as either objective function or constraint for the optimization calculations. In this thesis, as it is mentioned before, the root mean square of the radiated sound power level (RMSL) is considered as the objective function for the optimization process.

The geometry of the initial design is shown in Fig. 6.1 in 2-dimensional view. All of nine design variables are constrained with the upper and the lower limits of 10 mm and -10 mm, respectively. The initial values of the design variables, i.e., ϑ_i ($i = 1,\ 2, \ldots,\ 9$), are (1.062, 7.518, -0.827, 3.687, -7.174, -3.145, -5.195, 9.259, -2.335), respectively.

Table 6.2 summarizes the results for the original flat plate. The RMSL of the initial design in the frequency range of interest 0-100 Hz is 38.93 dB, where the maximum radiated sound level of 69.1 dB can be found in the spectrum at the fundamental frequency 21.8 Hz. The LS spectrum of the initial design is also shown in various plots such as, e.g., Fig. 6.2.

Table 6.1: Properties of the original flat rectangular plate

Property	Value
RMSL	45.31 dB
Mass m	7.850 kg
Fundamental frequency f_1	4.9 Hz
Max. LS (at $f_1 = 4.9$ Hz)	80.56 dB

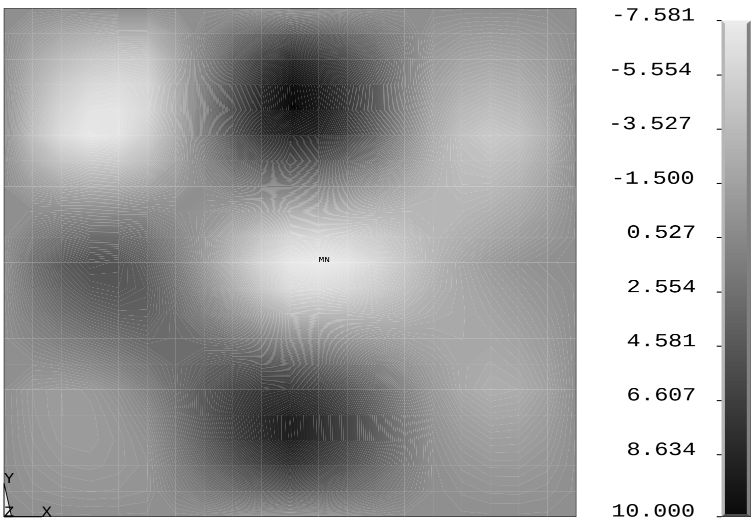

Figure 6.1: Initial design of the rectangular plate (values in mm).

Table 6.2: Properties of the initial design for the rectangular plate

Property	Value
RMSL	38.93 dB
Mass m	7.850 kg
Fundamental frequency f_1	21.8 Hz
Max. LS (at $f_1 = 4.9$ Hz)	69.1 dB

6.2 Optimization Results Considering One Set of Initial Design

6.2.1 Method of Feasible Directions

Fig. 6.2 shows that MFD could shift the first resonance peak to a higher frequency than the fundamental frequency of original plate.

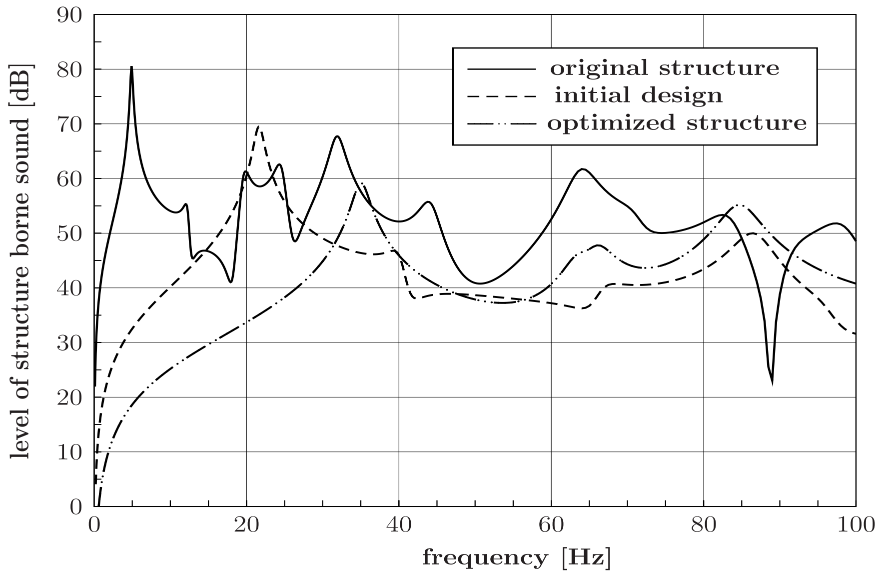

Figure 6.2: LS spectra of the original and the optimized rectangular plate (MFD).

The fundamental frequency f_1 of the original plate is 4.9 Hz, is firstly increased for the initial modified model up to 21.8 Hz and then for the final modified structure is increased to 34.7 Hz. The LS of the optimized structure is generally lower than the one of the original plate, which leads to a minimized RMSL.

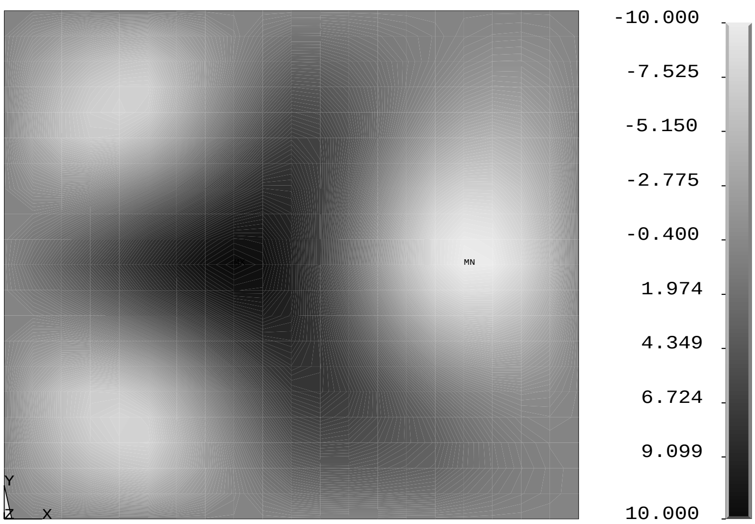

Figure 6.3: Geometry distribution of the modified rectangular plate (MFD, values in mm).

The contour plot of the plate's optimized geometry is shown in Fig. 6.3. The optimized geometry distribution can also be interpreted as a stiffening rib across the middle of the plate, which efficiently suppresses vibrations as well. The values in the spectrum on the righthand side of Fig.6.3 are in millimeters, i.e., dark areas indicate a geometry modification of up to 10 mm, whereas light zones represent a geometry modification of down to -10 mm.

Table 6.3 presents the optimization results for MFD after 500 function evaluations. The value of RMSL from the initial design is reduced by -10.63 dB to 28.3 dB for the finial optimized model. The maximum LS of the original plate is 80.56 dB at the fundamental frequency, whereas the one of the optimized structure is decreased by 21.85 dB to 58.71 dB at the new fundamental frequency. Interestingly, the number of natural frequencies within the frequency range of interest do not stay constant at 10, which means that the RMSL reduction using geometry modification concept is caused to shift the natural frequencies out of the frequency range of interest.

Table 6.3: Optimization results for Method of Feasible Directions

Property	Initial design	Optimized design
RMSL	38.93 dB	28.3 dB (-9.53 dB)
Minimum design modification	-7.174 mm	-10.00 mm
Maximum design modification	9.259 mm	9.37 mm
Fundamental frequency f_1	21.8 Hz	34.7 Hz (+12.9 Hz)
Maximum LS	69.1 dB	58.71 dB (-10.39 dB)
CPU time		8.33 h

6.2.2 Sequential Quadratic Programming

Fig. 6.4 shows the LS spectra for this method. The fundamental frequency f_1 of the original plate is 4.9 Hz, is firstly increased for the initial modified model up to 21.8 Hz and then for the final modified structure is increased to 41.7 Hz. The LS of the optimized structure is generally lower than the one of the original plate, which leads to a minimized RMSL.

The contour plot of the plate's optimized geometry is shown in Fig. 6.5. The optimized geometry distribution can also be interpreted as a stiffening rib across the middle of the plate, which efficiently suppresses vibrations as well. The values in the spectrum on the righthand side of Fig.6.3 are in millimeters, i.e., dark areas indicate a geometry modification of up to 10 mm, whereas light zones represent a geometry modification of down to -10 mm. There are eight domes on the modified model. These domes are diagonally located on the model. They can affect at least the first five normal mode shapes of the modified model.

Table 6.4 presents the optimization results for SQP method after 500 function evaluations. The value of RMSL from the initial design is reduced by -5.73 dB to 33.2 dB for the finial optimized model. The maximum LS of the original plate is 80.56 dB at the fundamental frequency, whereas the one of the optimized structure is decreased by 12.0 dB to 57.1 dB at the new fundamental frequency. Also, the new modified model has a fewer number of natural frequencies than the initial model in the frequency range of 0-100 Hz.

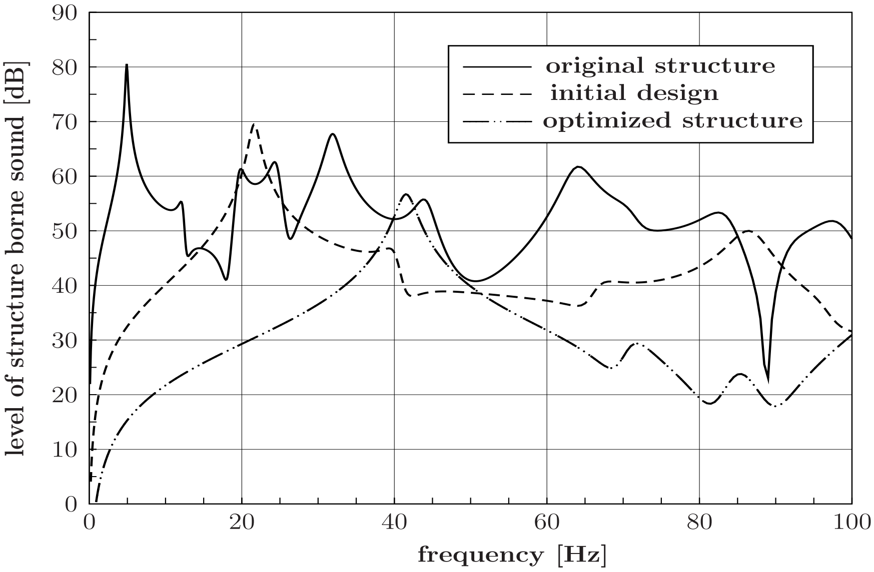

Figure 6.4: LS spectra of the original and the optimized rectangular plate (SQP).

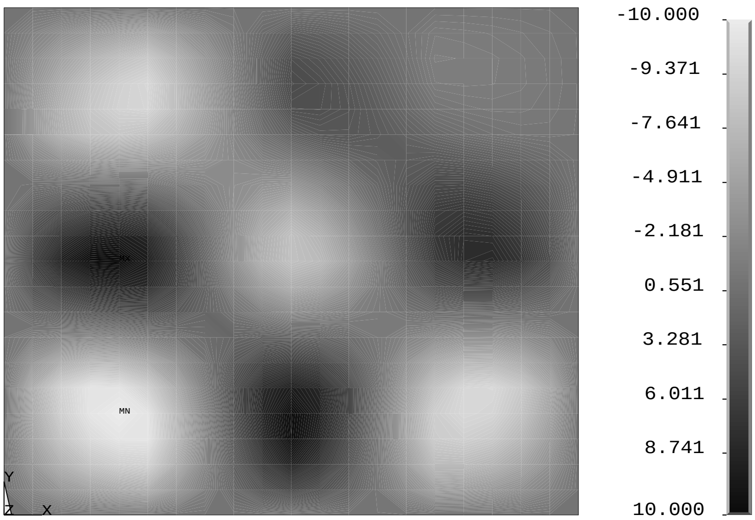

Figure 6.5: Geometry distribution of the modified rectangular plate (SQP, values in mm).

Table 6.4: Optimization results for Sequential Quadratic Programming method

Property	Initial design	Optimized design
RMSL	38.93 dB	33.2 dB (-5.73 dB)
Minimum design modification	-7.174 mm	-10.0 mm
Maximum design modification	9.259 mm	10.0 mm
Fundamental frequency f_1	21.8Hz	41.7 Hz (+19.9 Hz)
Maximum LS	69.1 dB	57.1 dB (-12.0 dB)
CPU time		8.33 h

6.2.3 Method of Moving Asymptotes

Fig. 6.6 shows that the first resonance peak is shifted to a higher frequency than the fundamental frequency of original plate. The fundamental frequency f_1 of the original plate is increased for the final modified structure to 27.5 Hz. The LS of the optimized structure is generally lower than the one of the original plate. The maximum LS of the optimized structure is decreased to 48.5 dB at the new fundamental frequency. The value of RMSL for the initial design is reduced by -16.98 dB to 21.95 dB for the finial optimized model.

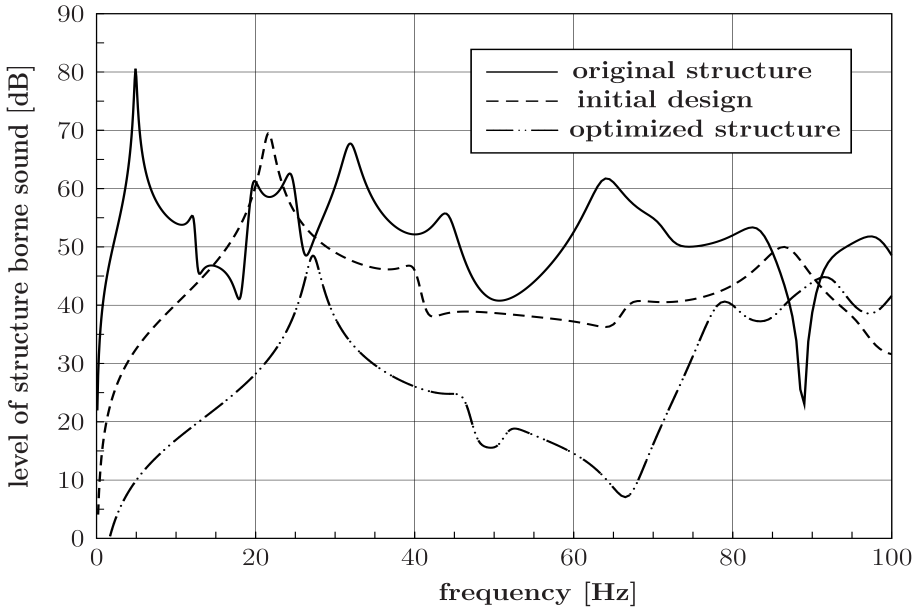

Figure 6.6: LS spectra of the original and the optimized rectangular plate (MMA).

Fig. 6.7 shows the modified geometry by MMA. The shape of modified rectangular plate has one dome in the middle of itself which can efficiently suppresses vibrations as well.

The optimization results for MMA is summarized in Table 6.5.

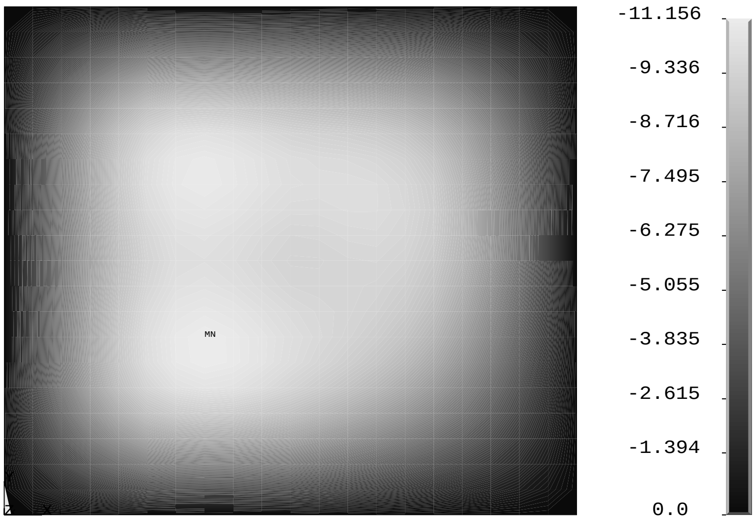

Figure 6.7: Geometry distribution of the modified rectangular plate (MMA, values in mm).

Table 6.5: Optimization results for Method of Moving Asymptotes

Property	Initial design	Optimized design
RMSL	38.93 dB	21.95 dB (-16.98 dB)
Minimum design modification	-7.174 mm	-10.0 mm
Maximum design modification	9.259 mm	0.0 mm
Fundamental frequency f_1	21.8 Hz	27.5 Hz (+5.7 Hz)
Maximum LS	69.1 dB	48.5 dB (-20.6 dB)
CPU time		8.33 h

6.2.4 Limited Memory BFGS Method for Bound Constrained Problems

Fig. 6.8 shows that the fundamental frequency f_1 initially increases for the initial modified model up to 21.8 Hz and then for the final modified structure increases to 37.9 Hz. The maximum LS of the original plate is 80.56 dB at the fundamental frequency, whereas the one of the optimized structure is decreased by 42.96 dB to 37.6 dB at the new fundamental frequency. The LS value is generally decreased in most of the frequency domain. The value of RMSL for the initial design is reduced by -4.86 dB to 34.07 dB for the finial optimized model. Furthermore, there are four new natural frequencies within the frequency range of interest for the final modified model.

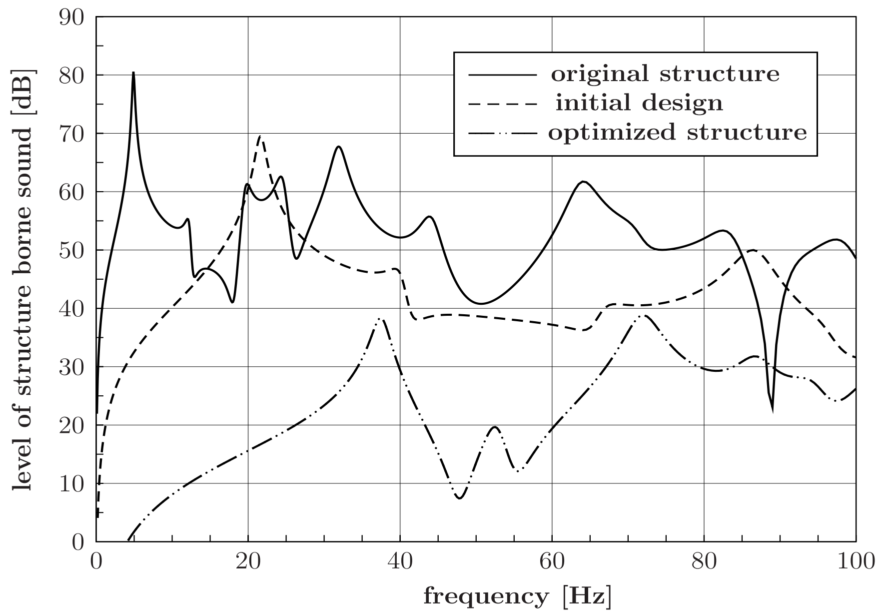

Figure 6.8: LS spectra of the original and the optimized rectangular plate (L-BFGS-B).

The modified model by L-BFGS-B method is drawn in Fig. 6.9. The contour plot of the plate's optimized geometry shows nine domes which are located almost uniformly and symmetric on the modified model. The optimized geometry distribution can also be interpreted as several stiffening ribs which affects most of mode shape of the model.

Table 6.6 indicates that this method has produced some infeasible results.

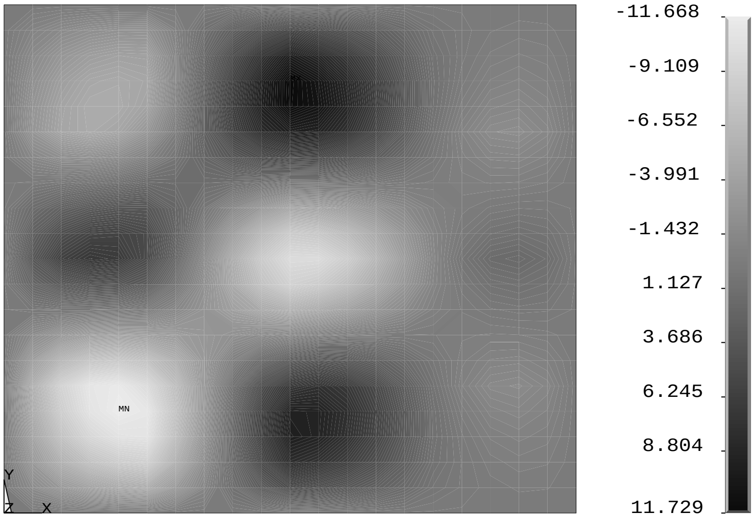

Figure 6.9: Geometry distribution of the modified plate (L-BFGS-B, values in mm).

Table 6.6: Optimization results for L-BFGS-B method

Property	Initial design	Optimized design
RMSL	38.93 dB	34.07 dB (-4.86 dB)
Minimum design modification	-7.174 mm	-10.0 mm
Maximum design modification	9.259 mm	10.0 mm
Fundamental frequency f_1	21.8 Hz	37.9 Hz (+16.1 Hz)
Maximum LS	69.1 dB	37.6 dB (-31.5 dB)
CPU time		8.33 h

6.2.5 Mid-Range Multi-Points Method

Fig. 6.10 shows the LS spectra for this method. The fundamental frequency f_1 of the original plate is 4.9 Hz, is firstly increased for the initial modified model up to 21.8 Hz and then for the final modified structure is increased to 41.2 Hz. The LS of the optimized structure is generally lower than the one of the original plate, which leads to a minimized RMSL.

The contour plot of the plate's optimized geometry is shown in Fig. 6.11. The optimized geometry distribution can be interpreted as a stiffening rib which efficiently suppresses vibrations as well.

Table 6.7 presents the optimization results for MMP after 500 function evaluations. The value of RMSL from the initial design is reduced by -23.43 dB to 15.5 dB for the finial optimized model. The maximum LS of the original plate is 80.56 dB at the fundamental frequency, whereas the one of the optimized structure is decreased by 31.3 dB to 37.8 dB at the new fundamental frequency. The number of natural frequencies within the frequency range of interest are lower than original and initial designs.

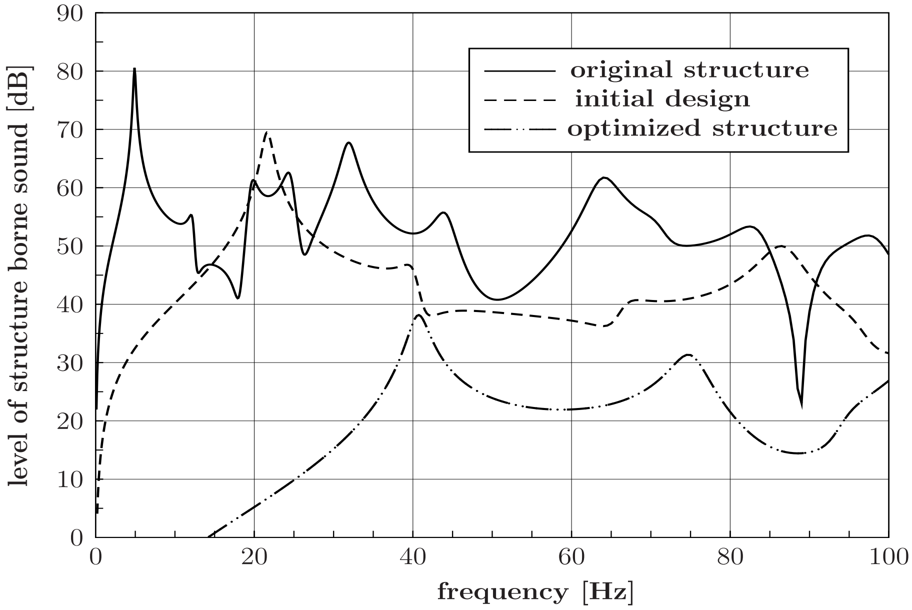

Figure 6.10: LS spectra of the original and the optimized rectangular plate (MMP).

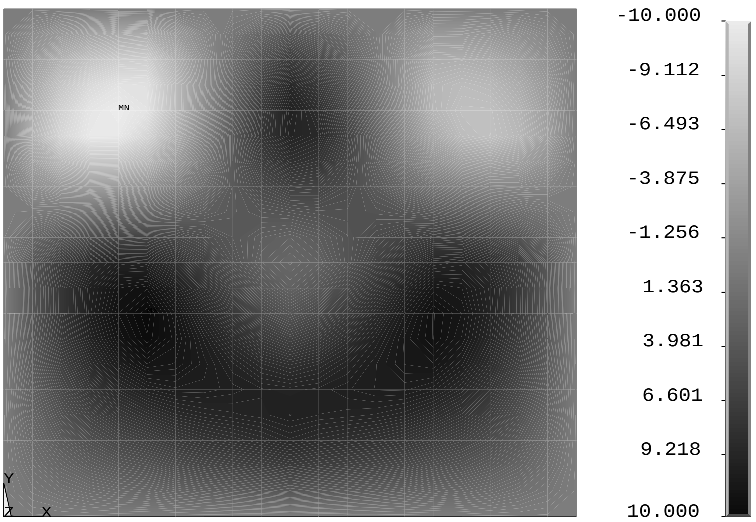

Figure 6.11: Geometry distribution of the modified rectangular plate (MMP, values in mm).

Table 6.7: Optimization results for Mid-Range Multi-Points Method

Property	Initial design	Optimized design
RMSL	38.93 dB	15.5 dB (-23.43 dB)
Minimum design modification	-7.174 mm	-10.0 mm
Maximum design modification	9.259 mm	10.0 mm
Fundamental frequency f_1	21.8 Hz	40.7 Hz (+18.9 Hz)
Maximum LS	69.1 dB	37.8 dB (-31.3 dB)
CPU time		8.33 h

6.2.6 Newton Method

Fig. 6.12 shows that the fundamental frequency f_1 is firstly increased for the initial modified model up to 21.8 Hz and then for the final modified structure is increased to 56.81 Hz. The maximum LS of the original plate is 80.56 dB at the fundamental frequency, whereas the one of the optimized structure is decreased by 9.4 dB to 59.7 dB at the new fundamental frequency. The LS value is generally decreased in most of the frequency domain. The value of RMSL for the initial design is reduced by -1.28 dB to 37.65 dB for the finial optimized model. Furthermore, there are two new natural frequencies within the frequency range of interest for the final modified model.

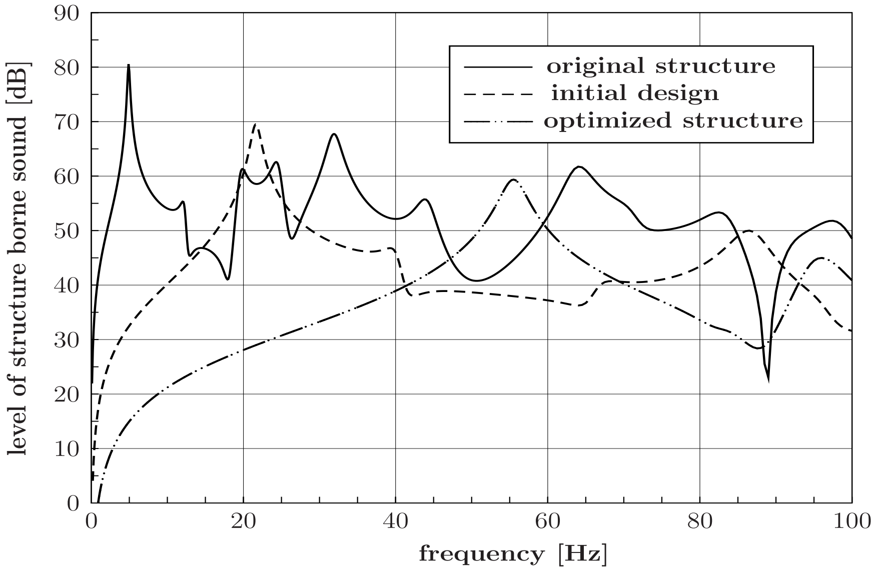

Figure 6.12: LS spectra of the original and the optimized rectangular plate (NM).

The contour plot of the plate's optimized geometry is shown in Fig. 6.13. The optimized geometry distribution can also be interpreted as a stiffening rib across the diagonal of the plate, which efficiently suppresses vibrations.

Table 6.8 presents the optimization results for NM. The optimum designs have violated the constraints.

Table 6.8: Optimization results for Newton method

Property	Initial design	Optimized design
RMSL	38.93 dB	37.65 dB (-1.28 dB)
Minimum design modification	-7.174 mm	-10.0 mm
Maximum design modification	9.259 mm	10.0 mm
Fundamental frequency f_1	21.8 Hz	56.81 Hz (+35.01 Hz)
Maximum LS	69.1 dB	59.7 dB (-9.4 dB)
CPU time		8.33h

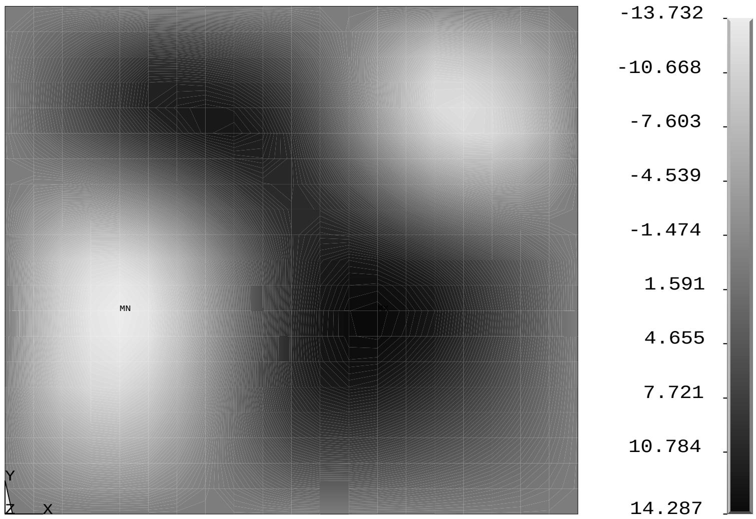

Figure 6.13: Geometry distribution of the modified rectangular plate (NM, values in mm).

6.2.7 Hybrid Design of Experiments

Fig. 6.14 shows the LS spectra for HDOE method.

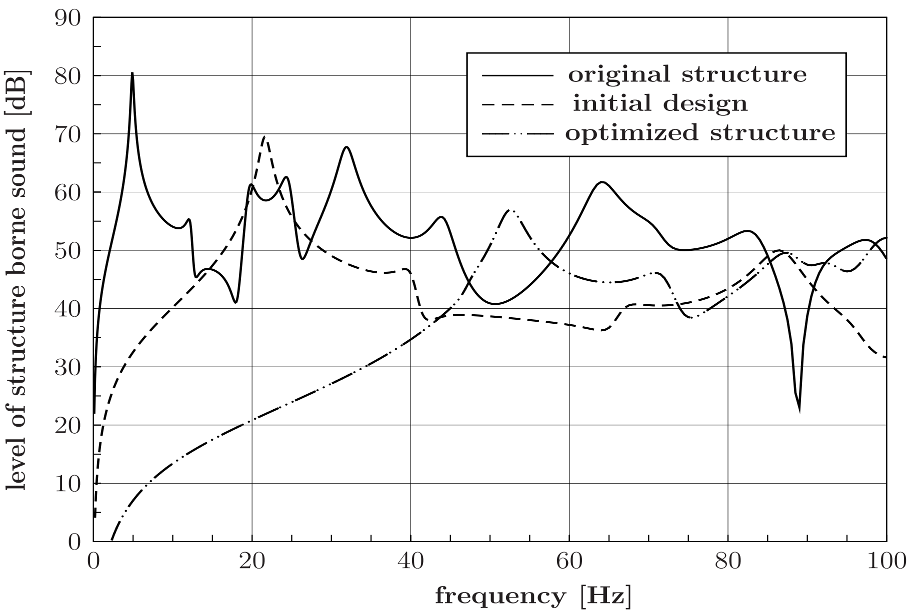

Figure 6.14: LS spectra of the original and the optimized rectangular plate (HDOE)

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Fig. 6.14 shows that the fundamental frequency f_1 is firstly increased for the initial modified model up to 21.8 Hz and then for the final modified structure is increased to 53.6 Hz. The maximum LS of the original plate is 80.56 dB at the fundamental frequency, whereas the one of the optimized structure is decreased by 12.6 dB to 56.5 dB at the new fundamental frequency. The value of RMSL for the initial design is reduced by -2.42 dB to 36.51 dB for the finial optimized model.The LS value is almost decreased in most of the frequency domain. This considerable reduction in the value of maximum LS is mainly caused

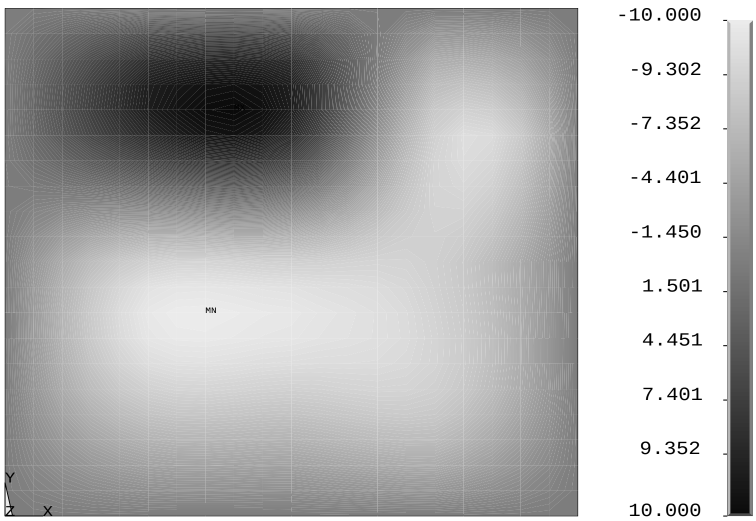

Figure 6.15: Geometry distribution of the modified rectangular plate (HDOE, values in mm).

Table 6.9: Optimization results for HDOE

Property	Initial design	Optimized design
RMSL	38.93 dB	36.51 dB (-2.42 dB)
Minimum design modification	-7.174 mm	-10.0 mm
Maximum design modification	9.259 mm	10.0 mm
Fundamental frequency f_1	21.8 Hz	53.6 Hz (+31.8 Hz)
Maximum LS	69.1 dB	56.5 dB (-12.6 dB)
CPU time		8.33 h

by a suitable control parameter setting in HDOE algorithm. There are also about five new natural frequencies within the frequency range of interest for the final modified model.

The contour plot of the plate's optimized geometry is shown in Fig. 6.7. The optimized geometry distribution can also be interpreted as a stiffening rib across the diagonal of the plate, which efficiently suppresses vibrations.

The optimization results for HDOE is summarized in Table 6.9.

6.2.8 Hybrid Neural Networks

Fig. 6.16 shows the LS spectra for HNN method when 110 objective function evaluations are performed . The maximum LS of the optimized structure is decreased to 54.9 dB at the new fundamental frequency. The value of RMSL for the initial design is reduced by -5.83 dB to 33.1 dB for the finial optimized model.

The contour plot of the plate's optimized geometry is shown in Fig. 6.17. The optimized geometry distribution can also be interpreted as a stiffening rib across the diagonal of the plate, which efficiently suppresses vibrations.

Table 6.10 lists the summary of optimization results from HNN method.

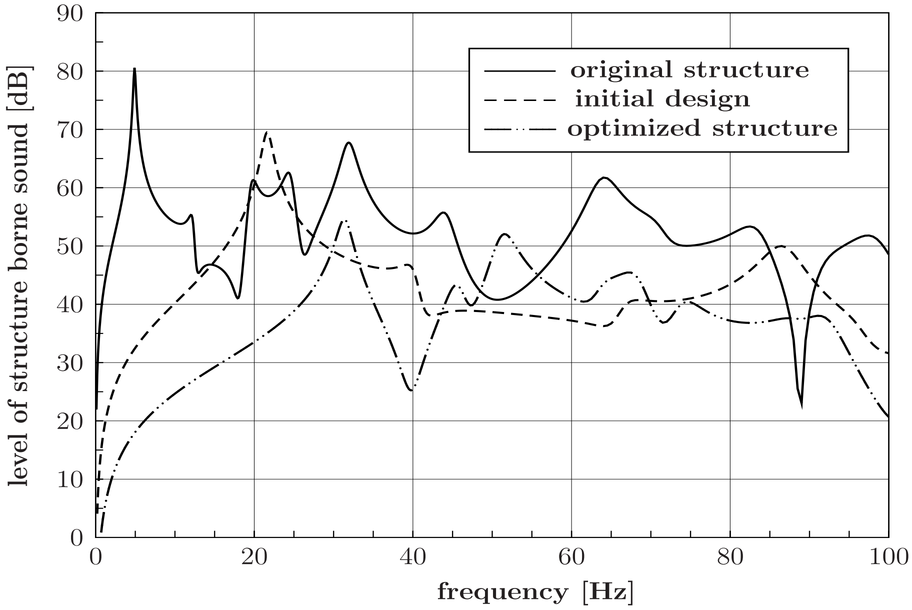

Figure 6.16: LS spectra of the original and the optimized rectangular plate (HNN).

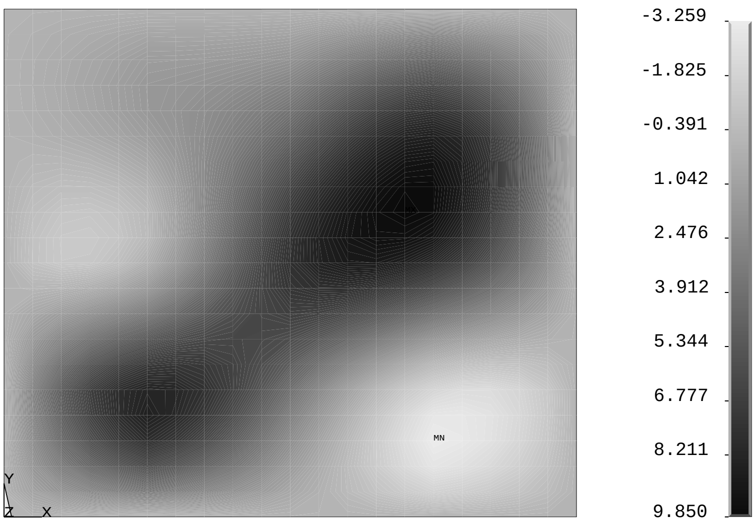

Figure 6.17: Geometry distribution of the modified rectangular plate (HNN, values in mm).

Table 6.10: Optimization results for Hybrid Neural Networks

Property	Initial design	Optimized design
RMSL	38.93 dB	33.1 dB (-5.83 dB)
Minimum design modification	-7.174 mm	-3.258 mm
Maximum design modification	9.259 mm	9.850 mm
Fundamental frequency f_1	21.7 Hz	32.8 Hz (+11.1 Hz)
Maximum LS	69.1 dB	54.9 dB (-14.2 dB)
CPU time		$\approx$ 1.86 h

6.2.9 Simulated Annealing Method

Fig. 6.19 shows that the first resonance peak is shifted to a higher frequency than the fundamental frequency of original plate. The fundamental frequency f_1 of the original plate, is firstly increased for the initial modified model up to 21.8 Hz and then for the final modified structure is increased to 31.9 Hz.

The LS of the optimized structure is generally lower than the one of the original plate, which leads to the minimized RMSL. The maximum LS of the original plate is 80.56 dB at the fundamental frequency, whereas the one of the optimized structure is decreased by 8.3 dB to 60.8 dB at the new fundamental frequency. The value of RMSL for the initial design is reduced by -4.73 dB to 34.2 dB for the finial optimized model.

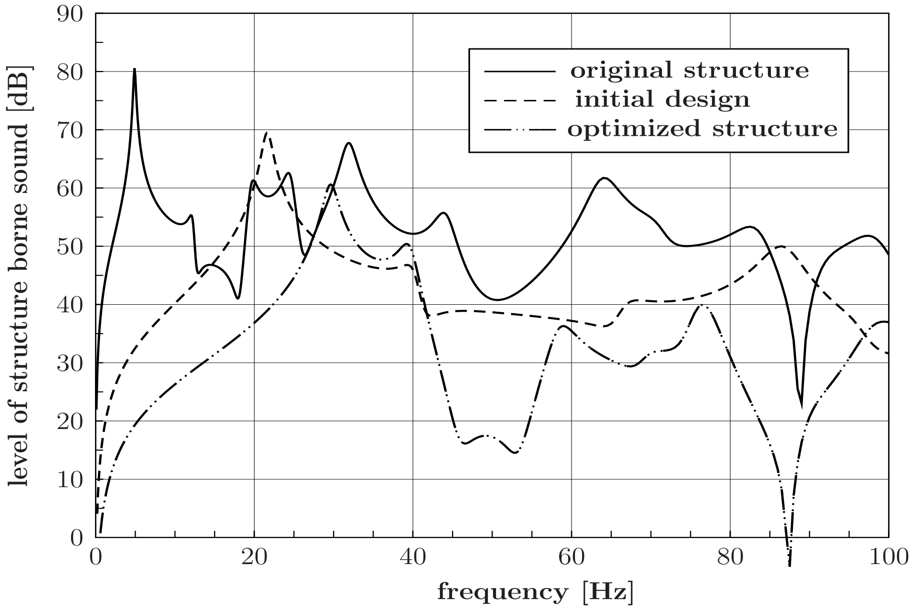

Figure 6.18: LS spectra of the original and the optimized rectangular plate (SA).

The optimization results for SA method is summarized in Table 6.11.

Table 6.11: Optimization results for Simulated Annealing method

Property	Initial design	Optimized design
RMSL	38.93 dB	34.2 dB (-4.73 dB)
Minimum design modification	-7.174 mm	-7.485 mm
Maximum design modification	9.259 mm	9.02 mm
Fundamental frequency f_1	21.8 Hz	31.9 Hz (+10.1 Hz)
Maximum LS	69.1 dB	60.8 dB (-8.3 dB)
CPU time		8.33 h

Fig. 6.19 shows the contour plot of the plate's optimized geometry. The new modified geometry distribution can also be interpreted as a stiffening rib in the middle of plate, which efficiently suppresses vibrations as well.

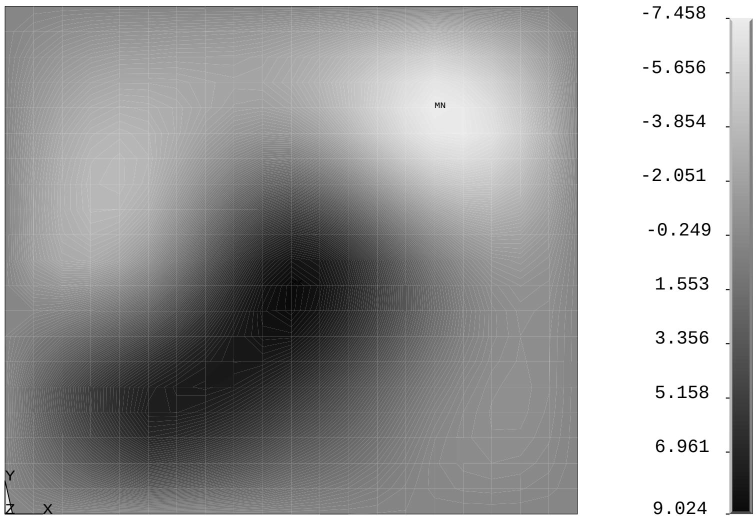

Figure 6.19: Geometry distribution of the modified rectangular plate (SA, values in mm).

6.2.10 Tabu Search Method

Fig. 6.20 shows the reduction of sound power level for Tabu Search method. The fundamental frequency f_1 of the modified model is increased to 31.2 Hz. The maximum LS of the optimized structure is decreased to 55 dB at the new fundamental frequency. Interestingly, the number of natural frequencies within the frequency range of interest is reduced to three. Also, The value of RMSL for the initial design is reduced by -10.33 dB to 28.6 dB for the finial optimized model.

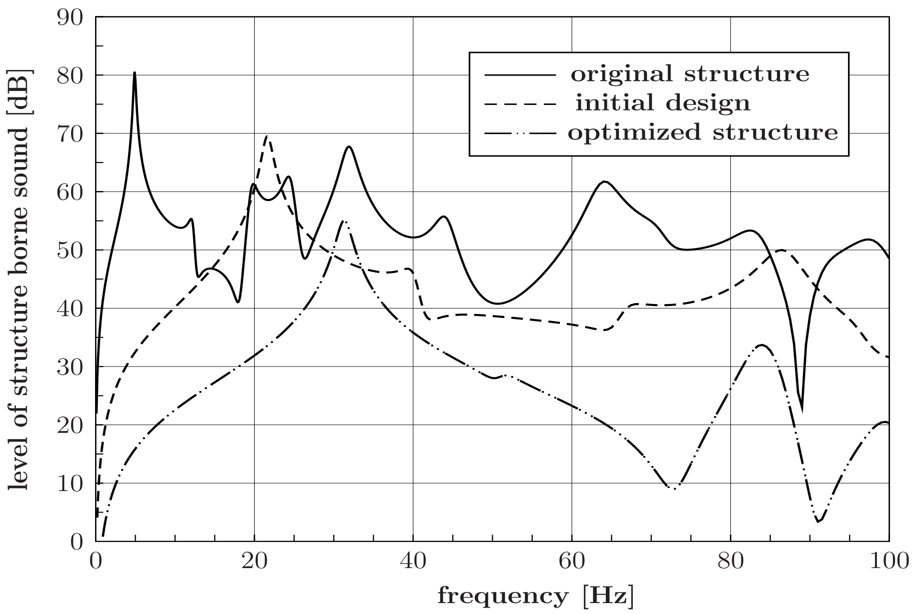

Figure 6.20: LS spectra of the original and the optimized rectangular plate (TS).

The contour plot of the plate's optimized geometry is shown in Fig. 6.21. The optimized geometry distribution can also be interpreted as a stiffening rib across the diagonal of the plate, which efficiently suppresses vibrations.

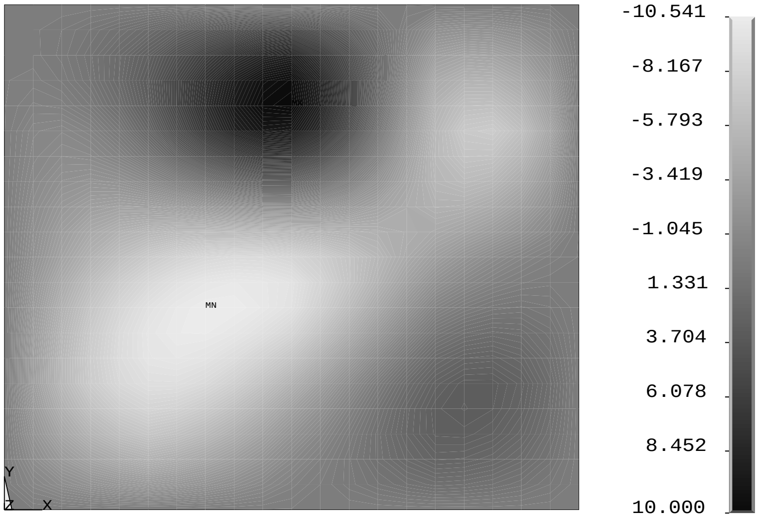

Figure 6.21: Geometry distribution of the modified rectangular plate (TS, values in mm).

Table 6.12: Optimization results for Tabu Search method

Property	Initial design	Optimized design
RMSL	38.93 dB	28.6 dB (-10.33 dB)
Minimum design modification	-7.174 mm	-10.0 mm
Maximum design modification	9.259 mm	10.0 mm
Fundamental frequency f_1	21.8 Hz	31.2 Hz (+9.4 Hz)
Maximum LS	69.1 dB	55. dB (-14.1 dB)
CPU time		8.33 h

Table 6.12 indicates that there is a constraint violation of -0.541 mm for the minimum geometry modification value.

6.2.11 Controlled Random Search Method

Fig. 6.22 shows that the fundamental frequency f_1 is firstly increased for the initial modified model up to 21.8 Hz and then for the final modified structure is increased to 31.3 Hz. The maximum LS of the original plate is 80.56 dB at the fundamental frequency, whereas the one of the optimized structure is decreased by 11.8 dB to 57.3 dB at the new fundamental frequency. The number of natural frequencies is decreased for the modified model. The value of RMSL for the initial design is reduced by -5.23 dB to 33.7 dB for the finial optimized model. Furthermore, the LS spectra of the modified model is generally lower than the LS spectra of the original plate.

The contour plot of the plate's optimized geometry is shown in Fig. 6.23. The optimized geometry distribution can also be interpreted as a U-shape stiffening rib in the middle of the plate, which efficiently suppresses vibrations.

The optimization results for CRSM method is summarized in Table 6.13.

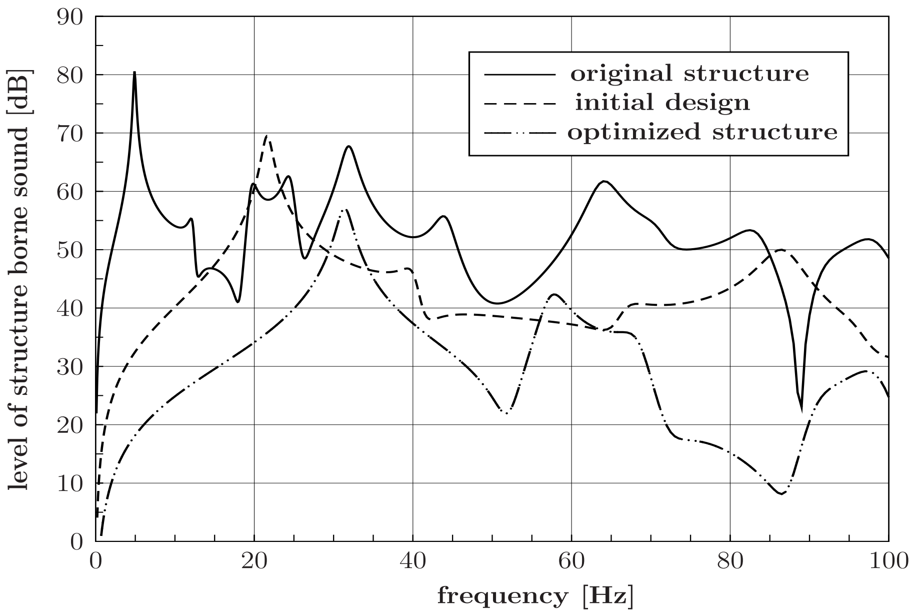

Figure 6.22: LS spectra of the original and the optimized rectangular plate (CRSM).

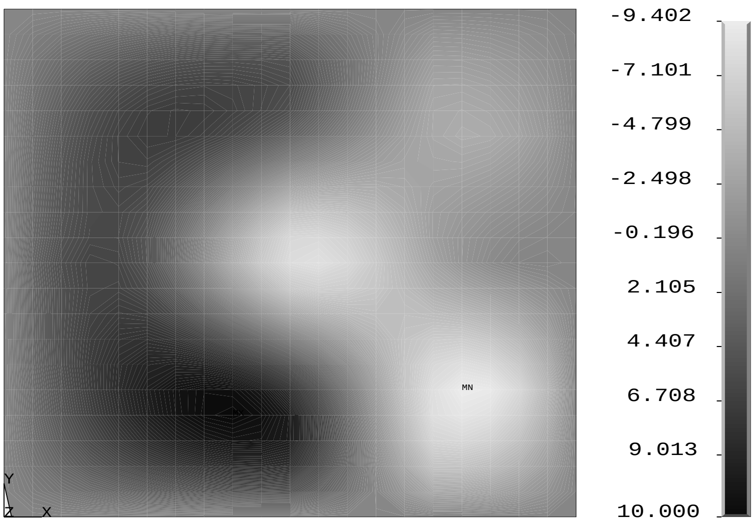

Figure 6.23: Geometry distribution of the modified rectangular plate (CRSM, values in mm).

Table 6.13: Optimization results for Controlled Random Search Method

Property	Initial design	Optimized design
RMSL	38.93 dB	33.7 dB (-5.23 dB)
Minimum design modification	-7.174 mm	-9.402mm
Maximum design modification	9.259 mm	10.0 mm
Fundamental frequency f_1	21.8 Hz	31.3 Hz (+9.5 Hz)
Maximum LS	69.1 dB	57.3 dB (-11.8 dB)
CPU time		8.33 h

6.3 Optimization Results for Genetic Algorithm Method

A set of initial population including of 20 members and 25 total regenerations are considered for the optimization by GA method. The average value of RMSL of these 20 initial design sets is 40.71 dB. The iteration history in this case is shown in Fig. 6.24.

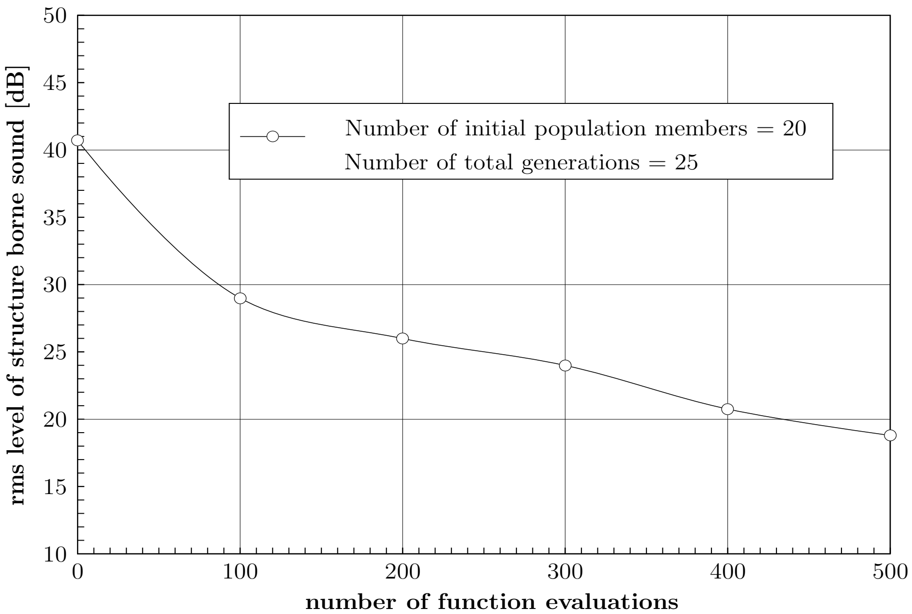

Figure 6.24: Reduction of RMSL by GA method.

The LS spectra which is also shown in Fig. 6.14. The best optimum design in this case, is shown in Fig. 6.26. The fundamental frequency f_1 is increased for the final modified structure to 37.4 Hz. The maximum LS of the optimized structure is decreased to 37.9 dB at the new fundamental frequency. GA method could minimize the radiated sound power level in all of the frequency domain. The value of RMSL is decreased to 18.5 dB for the finial optimized model.

Fig. 6.26 shows the contour plot of the plate's optimized geometry. The new geometry distribution can be interpreted as a stiffening rib across the diagonal of the plate.

Table 6.14 presents the optimization results for GA method.

Table 6.14: Optimization results for Genetic Algorithms method

Property	Optimized design
RMSL	18.5 dB
Minimum geometry modification	-10.0 mm
Maximum geometry modification	10.0 mm
Fundamental frequency f_1	37.4 Hz
Maximum LS	37.9 dB
CPU time	8.33 h

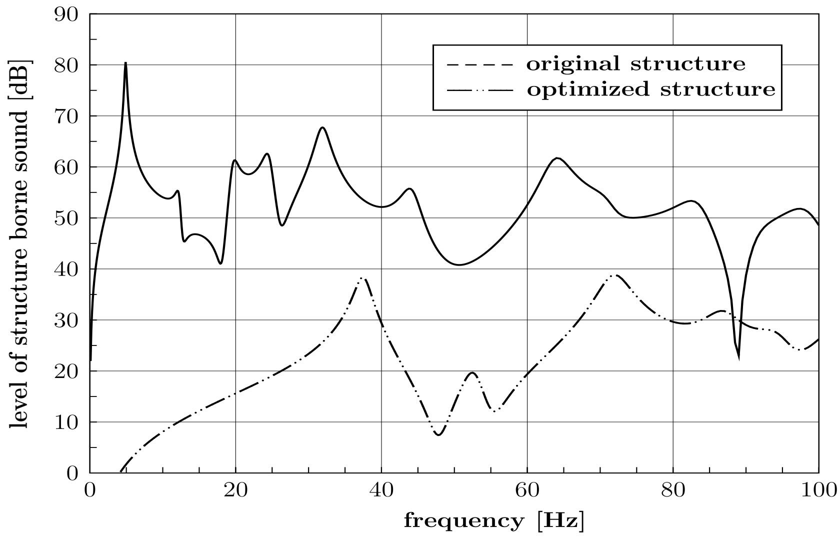

Figure 6.25: LS spectra of the original and the optimized rectangular plate (GA).

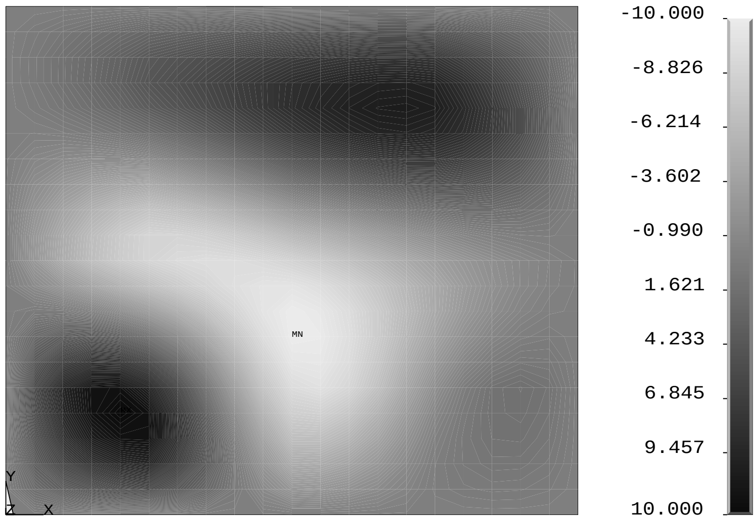

Figure 6.26: Geometry distribution of the modified rectangular plate (GA, values in mm).

6.4 Summary of Optimization Results Considering of 1000 Design Sets

6.4.1 Iteration History of Methods

Summaries of typical iteration histories for some optimization methods is depicted in Fig. 6.27. Curves in this graph are drawn based on the supports between 0 and 500 (in steps of 100) function evaluations. The RMSL value shown in Fig. 6.27 is the averaged value of 1000 design sets during the optimization process. In fact, the value of RMSL is an average value in each function evaluation over the 1000 design sets. The initial averaged RMSL for these 1000 initial design sets is 42.7 dB.

The convergency rate factor, i.e., ψ, for various optimization approaches is calculated by

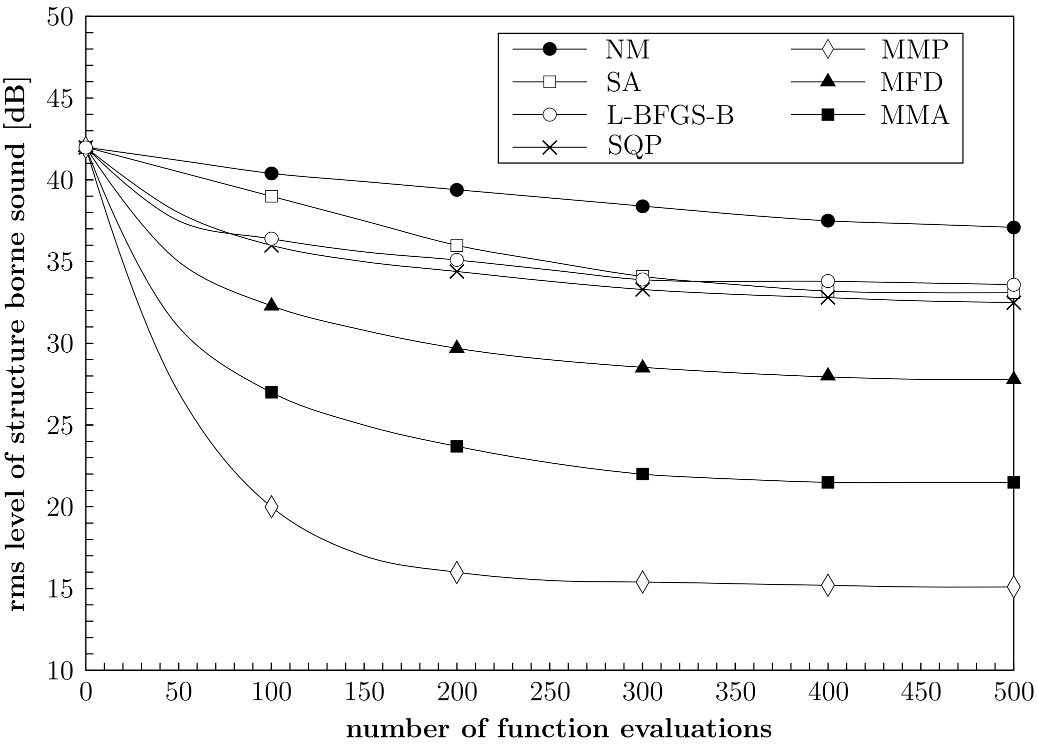

Figure 6.27: Minimization of RMSL by different optimization methods.

Eq. (6.1),

$$\psi = \frac{\left|\overline{\mathcal{F}_{\text{start}}} - \overline{\mathcal{F}_{\text{fnvs}}}\right|}{\text{fnvs}}, \tag{6.1}$$

where $\overline{\mathcal{F}_{\text{start}}}$ and $\overline{\mathcal{F}_{\text{fnvs}}}$ are the average value for the initial and the final objective function values after a specific number of function evaluations (in this case fnvs=500), respectively.

The convergence rate ψ can be interpreted as the value of averaged RMSL reduction per each function evaluation. This parameter represents the speed of an optimization method. Indeed, it can be important as it provides some guidelines about the amount of time which should be invested to expect a specific reduction in the value of RMSL.

Table 6.15 presents the overall classification of optimization methods with respect to their convergence rates. It is shown that various combinations of approximation and optimization methods can be categorized generally as fast, medium and slow. MMA and MMP are reported as fast which means these methods can give the greatest value of objective function reduction per each function evaluation among all of optimization methods which are considered for this study.

Table 6.16 summarizes the optimization results for various optimization methods when one initial design set and maximum 500 objective function are considered. The value of RMSL reduction, i.e., ΔRMSL, and the value shifting to a higher fundamental frequency, i.e., Δf_1, are collected in this table. The value of ΔRMSL is simply calculated from the difference of initial and optimum RMSL values. The most reduction in the value of RMSL is achieved by MMP, i.e., -23.43 dB. The lowest value of RMSL reduction after performing of 500 function evaluations is reported for NM with -1.28 dB. Also, NM could shift the fundamental frequency of modified model to the highest value, i.e., +56.81 Hz in comparison with other optimization methods. Furthermore, HDOE could give a considerable shifting

Table 6.15: Convergence rates of various combined optimization algorithms.

Category (Convergence Rate)	Optimization Method	Approximation Method
Fast ($0.04 < \psi$)	MMA	Taylor Series
	MMP	DOE+Taylor Series
Medium ($0.02 < \psi \leq 0.04$)	MFD	Taylor Series
Slow ($\psi \leq 0.02$)	NM	Taylor Series
	L-BFGS-B	Taylor Series
	SQP	Taylor Series
	SA	-

value for the fundamental frequency, i.e., +31.8 Hz.

6.5 Robustness of the Methods

Du et al. [Du 06] indicated that the reliability based design optimization (RBDO) method is prevailing in stochastic structural design optimization by assuming the amount of input data is sufficient enough to create accurate input statistical distribution.

If the sufficient input data cannot be generated due to limitations in technical and/or facility resources, the possibility-based design optimization (PBDO) method can be used to obtain reliable designs by utilizing membership functions for epistemic uncertainties.

For RBDO, the performance measure approach (PMA) is well established and accepted by many investigators. It is found that the same PMA is a very much desirable approach also for the PBDO problems.

This section proposes to use a similar approach to PBDO for design optimization. The performances of success in % for several optimization methods those begin their optimization process from a same set of initial designs, i.e., MFD, NM, L-BFGS-B method, SQP method, MMA, MMP method and SA method, are calculated. This success rate is determined based on RMSL reduction after a specific number of objective function evaluations. For analysis of optimization results, the success rate is measured in percent.

The success rate represents the ratio between the number of initial designs resulting in a specific improvement of the objective function over the 1000 considered initial design sets after a certain number of objective function evaluations. The entire number of optimization runs is M.

Table 6.17 presents the success rates for seven optimization methods, three selections of M and five different levels of objective function reduction.

It is obvious that all these local methods are quite successful to decrease the objective function. However, only one method, i.e. MMA, was capable to always gain an improvement of at least 5 dB. MMA turns out to be very successful up to at least 15 dB improvement. Note that even after 200 function evaluations, every second MMA run reached an impact

Table 6.16: Summary of optimization results after maximum 500 objective function evaluations.

Algorithm	Maximum LS (dB)	Fundamental frequency f_1 (Hz)	Δf_1 (dB)	RMSL (dB)	ΔRMSL
MFD	58.71	34.7	+12.9	28.3	-9.53
SQP	57.1	41.7	+19.9	33.2	-5.73
MMA	48.5	27.5	+5.7	21.95	-16.98
L-BFGS-B	37.6	37.9	+16.1	34.07	-4.86
MMP	37.8	40.7	+18.9	15.5	-23.43
NM	59.7	56.81	+35.01	37.65	-1.28
HDOE	56.5	53.6	+31.8	36.51	-2.42
SA	60.8	31.9	+10.1	34.2	-4.73
TS	55.0	31.2	+9.4	28.6	-10.33
CRSM	57.3	31.3	+9.5	33.7	-5.23

Table 6.17: Success rate (in %) of optimization methods after fixed number of objective function. evaluations

		Success rate for minimum gain of				
M	Method	5 dB	10 dB	15 dB	20 dB	25 dB
100	L-BFGS-B	85	68	34	0	0
	MFD	72	30	6	1	0
	MMA	100	74	30	3	0
	MMP	61	34	16	8	4
	NM	58	34	1	0	0
	SA	25	6	0	0	0
	SQP	83	68	31	0	0
200	L-BFGS-B	86	68	36	1	0
	MFD	83	43	9	3	0
	MMA	100	82	53	8	0
	MMP	64	39	17	13	7
	NM	60	35	1	1	0
	SA	46	9	2	0	0
	SQP	83	68	31	7	0
500	L-BFGS-B	86	68	39	2	0
	MFD	83	47	14	5	0
	MMA	100	91	70	15	0
	MMP	69	50	23	20	9
	NM	63	38	4	4	2
	SA	82	15	3	0	0
	SQP	83	68	31	12	0

Table 6.18: List of computers available for parallel computation.

Hostname	Type	CPU	RAM	Operating system
Phobos	PC farm Linux Network	AMD Opteron 2,2 GHz	4 GB per CPU	Suse Enterprise Server 9
Merkur	SGI Altix 3700	Intel Itanium II 1,5 GHz	4 GB per CPU	Suse Enterprise Server 9

of 15 dB and more. In this sense, MMA is a very reliable optimization method. However, even the L-BFGS-B and SQP seem to be reliably supply reasonable gains after only 100 function evaluations. However, it does not seem reasonable to let them run longer since further improvement is rather low.

Note that even after 200 function evaluations, every second MMA run reached an impact of 15 dB and more. In this sense, MMA is a very reliable optimization method. However, even the L-BFGS-B and SQP seem to be reliably supply reasonable gains after only 100 function evaluations. However, it does not seem reasonable to let them run longer since further improvement is rather low. MMP appears as a remarkable method. As shown in Fig. 6.27, MMP may converge to extremely low levels of the objective function. On the one hand, this is confirmed by the success rate since it is the most successful method to find very large improvements of the objective function. On the other hand, the overall success rate, e.g. to achieve at least 5% improvement is rather low. Large gains are reported for NewtonŠs method but the overall success rate is even much lower than for MMP. MFD performs well to achieve a 5 and 10 dB gain within only 100 function evaluations but afterwards it seems to get stuck. The stochastic SA is slow but robust. As can be seen in Table 6.17, the success rate to achieve 5 dB is acceptable but the method is converging much slower than the other six. Most likely, SA will provide excellent gains after a large number of function evaluations.

6.6 Parallelizing

It is possible to carry out the computations on several CPUs in parallel when using the optimization algorithms. This does not mean that optimization program code itself is parallelized, but rather are the independent optimization computations distributed to several CPUs. Indeed the separate optimization attempts, which are started from separate initial designs, are distributed on several CPUs to collect more optimization results than when just one CPU is used to carry out the sequential optimization processes.

Table 6.18 lists all the computers that were used for parallel computation.

Two parallelizing methods as sequential (trivial) and master and slaves approaches are used. Because the optimization time for each independent optimization attempt is not always a same, therefore the trivial approach is not effective. However the master and slave method can solve this problem because the central CPU (master) controls the other CPUs (slaves) to coordinate the total optimization process by managing of the distribution of optimization jobs in between the CPUS. In this case, a central control routine, which runs on master CPU, distributes the various input files one after another to the slave CPUs that are available for parallel computation. Then the FE analysis of the respective individual input file is started using ANSYS. When a particular ANSYS job on one of the CPUs is finished, it creates a file in a special directory on the host computer. This allows the control routine to determine which computation job is done, if that ANSYS job exited without errors, and how much time that ANSYS job consumed. Master and slave parallel programming method has showed better performance than trivial MPI approach. However, if the optimization codes can be parallelized to perform the objective function, gradient and constraints evaluations in a same time on the several CPUs, it can reduce to total optimization time.

The computation time for each function evaluation takes about 65 seconds on a SGI 3700 Altix computer. Typically, the FE analyses take around 90% of the total CPU time (insert the CPU time demo), whereas the calculation of the objective function value and constraints take around only 10% of the computation time. In most of the optimization algorithms except GA, the FE computations and the calculation of the objective function and constraint values must be done sequentially because each new design proposal depends on the previous optimization history and success. In contrast, GA allows parallel FE computations because the new design parameters hardly depend on previous results.

Chapter 7

Conclusions and Future works

In this last section, the conclusions and future works are discussed.

7.1 Conclusions

It has been shown that the optimization procedures used in this study are able to produce significant improvements of the objective function. This holds for all of the optimization algorithms employed. These methods can be used for numerical optimization in structural acoustics and it can be expected to achieve acceptable results after a certain number of function evaluations. However, they are recommended to be implemented in hybrid optimization algorithms.

The geometry of the objective function is unknown but it can be understood that the objective function is highly nonlinear and there are several local and global minima in the design region. This is clearly indicated since many optimization runs have virtually converged and, depending on initial parameter set and method, they stuck at very different optimal parameter sets.

The result of Newton method depends on the property of the Hessian matrix. If the Hessian is not positive definite, we cannot expect to get a good optimization result. Herein, the Hessian is calculated by finite differences and it is assumed that it is symmetric. Possibly, evaluation of the Hessian may have introduced a numeric error which is due to numeric differentiation which may slow down this method. Similar approximations of the Hessian for the L-BFGS-B and SQP may be the reason for performing similarly and, in particular, for SQP to perform less reliable than MMA and MMP.

The method of moving asymptotes is a method with automatically controlled step size. This may be one reason why this method is that robustly finding substantial improvements of the objective function.

The mid-range multi point method is the only method to use a nonlocal approximation scheme. This may be the reason why this method shows the best performance in finding very quiet designs. Unfortunately, this method is not reliably finding large gains.

The use of splines has make it possible to model the structure's geometry distribution with just a few key points rather than with many FE nodes, which drastically reduces the computation time.

The main part of computation time in optimization process has been consumed by FEA part of optimization procedure for the calculation of surface nodal velocities of the FE model. At this regard, it is possible to carry out the computations on several CPUs in parallel when using the optimization algorithms. Although parallel programming techniques can sometimes reduce the total computation time but they have actually no effect on the required CPU time for each single objective function evaluations. The main part of optimization time is consumed by FE calculations.

The optimization procedure is a combination of the commercially available FE software ANSYS and user-written programs. Due to the modular structure of the procedure it should be easy to replace this FE software with any other FE program. Likewise, it should be possible to implement an alternative optimization algorithm.

CRSM can be used to produce some suitable initial designs for considering in other gradient-based optimization methods.

Since the tuning of initial parameters for HDOE and HNN has been done in a tray and error manner, it is actually not possible to make a general conclusion about their convergence rates. However, HDOE and HNN are able to reduce the RMSL of objective function. HDOE with linear approximation of objective function is always recommendable for implementing in structural acoustics optimization applications. The calculation of virtual objective function values by the trained NN is very fast. It takes just a few milliseconds. Therefore, in comparison with other methods, HNN is relatively fast and can produce acceptable optimization results. But, designing of an efficient NN depends on the type of the problem and the experience of the user and sometimes with a trial and error approach. Then, it is necessary to do more researches in this field.

The nature of TS method is to explore the entire of the design domain (diversification) and then to focus on most promising areas to find the best optimum designs (intensification). This overwhelming process makes the TS method in general a slow optimization method.

Although, there is an intent to develop some complex hybrid optimization algorithms to reduce the total optimization time and to improve the quality of optimization results, but as the results of this study showed, it seems that the powerful optimization methods like MMA and MMP can produce good results too. There are a number of strategies to create hybrid optimization methods. It is one concept to start with a global search algorithm, continue with a mid-range method and complete the optimization run by using a local method. Another strategy could be to use several initial designs and thus several optimization paths. An industrial scenario could be that there is CPU time for 10^4 function evaluations. Then, for our case, it is particularly promising to run the MMP 100 times with 100 function evaluations each. If there is only time for 500 function evaluations, it might be more reasonable to rely on MMA and either one optimization with 500 function evaluations or, eventually two runs with 200 and one with 100 function evaluations.

The main part of the optimization process is consumed by the structural acoustic analysis while the objective function is evaluated. Therefore, it is sensible to work on fast methods for this part of the analysis. However, knowledge of methods to find a good design very quickly will be relevant for optimization purposes as well. But no doubt, decreasing the time for one function evaluation by 50 percent, will allow to evaluate it twice as often within a fixed prescribed time.

7.2 Future works

Although this study addresses a lot of issues there are still a lot left to be done and many problems still wait to be solved.

Though it is assumed that an RMSL reduction leads to a noise reduction, i.e. to a reduction of the total radiated sound power, this assumption has not been validated in the present work. Therefore, the radiated sound power of the optimized designs should be compared with that of the initial design to see whether a significant RMSL reduction results in a significant reduction of the radiated sound power as well. As the RMSL is a similar measure a the equivalent radiated sound power in [Fritze 09], the example can be compared with the floor panel in that paper. However, the the answer to the question whether a reduced RMSL will lead to a reduced radiated sound power has no impact on the performance of the optimization methods.

It should be checked if the optimization algorithms used in this study can either be modified and improved such that they achieve better results with shorter computation times. Although the methods and procedures presented in this work are quite effective and relatively efficient, they are certainly not the essence of all wisdom. Clearly, the implementation is another crucial issue for fast and reliable convergence.

Combinations of well performing optimization methods should be experienced to see whether they can give a significant improvement of RMSL with the fewest number of function evaluations or not. In this case, finding the most effective switching strategies for hybrid robust optimization algorithms in structural acoustics is an open research area which should be further investigated.

Some methods like the Neural Networks and Design of Experiments have the potential for more explorations.

This comparative study should be performed on other real-world and industrial applications to see their performances in such cases.

Usage of effective sensitivity analysis methods can reduce the computation time and it can be investigated as the continuation of this current study.

Different objective functions should be experienced as well. For example, the structure could be optimized to minimize transmissibility on different frequencies of interest, or could be optimized to maximize sound absorption in particular frequencies. Thus, the problem could be recast as a multiple objective optimization problem and other techniques can also be explored, e.g, Pareto front, goal programming, combination of the different objective functions as a single objective, optimizing one of the objective functions while keeping the other ones as constraint equations, etc.

Stochastic optimization techniques can also be used to recast the structural acoustic optimization as a robust optimization problem. For example, for a particular objective function, a second objective can be added as the standard deviation of this function. In this case, the robust optimization problem becomes a multi-objective problem.

Other constraint equations can also be considered, especially for the case where some relationship might exist between the design variables, e.g., the distance between any two design points on the structure, or between each of these points and the external boundary of the structure. Furthermore, other equalities and inequalities constraints that might be considered in the problem.

Appendix A

Some Remarks on the Implementation of Computer Programs

All of the optimization programs include a main program and some subroutines. In the main program, the user can perform the required primary settings for, e.g., the initial designs, the objective function, the bound constraints, the gradients, and the termination criterium. It is not necessary to alter any other parameters in the subroutines. The main program calls the subroutine(s) to perform the optimization process with respect to the initial settings. Then, the finial results will be written in the separate files.

A.1 Program for Method of Moving Asymptotes

The method of moving asymptotes (MMA) represents a family of convex approximation methods suitable for structural optimization problems. Its efficiency depends strongly on asymptote and move limit locations. The general algorithm of MMA can be described as follows:

Algorithm A.1 *MMA*

1. K=0.
2. Set ϑ_i^K, $\mathcal{F}(\boldsymbol{\vartheta})^K$, $g(\vartheta_i)^K$, $i = 1, \ldots, n$.
3. $P(\boldsymbol{\vartheta})^K = \mathcal{F}(\boldsymbol{\vartheta})^K + \sum(U_i - \vartheta_i^k)^2 g_i^k(\frac{1}{U_i - \vartheta_i} - \frac{1}{U_i - \vartheta_i^k}) + \sum(\vartheta_i^k - L_i)^2 g_i^k(\frac{1}{\vartheta_i - L_i} - \frac{1}{\vartheta_i^k - L_i})$.
4. Find $\boldsymbol{\vartheta}_*^K$ which minimize P^K.
5. Set $\vartheta_i^{K+1} = \vartheta_*^K$.
6. Check stopping criterion.
7. $K = K + 1$, go to 2.

The quantities L_i and U_i are called the moving asymptotes and can be thought of as move limits controlling the convexity of the approximation [van Houten 98, Svanberg 04]. In practice there is no general rule to find suitable values for the asymptotes. Setting $L_i = 0$ and $U_i = +\infty$ equals the convex linear approximation approach and with $L_i = -\infty$ and $U_i = +\infty$ a linear approximation results.

In each step of the iterative process, a strictly convex approximating sub-problem is generated and solved. The generation of these sub-problems is controlled by so called moving asymptotes, which may both stabilize and speed up the convergence of the general process.

The MMA optimization procedure uses from several FORTRAN, C and ANSYS script shells. The main optimization program is ksmaib.f and it uses from several subprograms, i.e., ksasymp.f, ksmaxim.f, ksmaxsu.f, ksmmasu.f and kstruss.f. The objective function calculation starts from the inside of kstruss.f using an interface, i.e., call_program.c that sends the input data to ANSYS solver. The modeling of structure, defining of its boundary conditions, and external excitations performed in an ANSYS file, i.e., ansysinp.dat. The finite element analysis carried out by ANSYS using this ansysinp.dat. A script shell can compile the FORTRAN and C programs and links them to each other to build an executive file. Then this executive file is ready for sending to a high performance computer for the finite element analysis by the ANSYS solver. Having objective function calculated, then the required data for the continuation of optimization process transfer automatically to the main FORTRAN program. If the termination criteria are satisfied, then the main program terminates the optimization process and writes the results in an output file. If the termination criteria are not satisfied, then the new start design variables are being read from a file, i.e., data20000.input, and the optimization will be repeated.

A.2 Program for Method of Feasible Directions

The minimization algorithm is based on Zoutendijk's method of feasible directions, [Vanderplaats 84] and [Zoutendijk 60]. The algorithm has been modified to improve efficiency and numerical stability and to solve optimization problems in which one or more constraints are initially violated [Vanderplaats 73]. While the program is intended primarily for the efficient solution of constrained functions, unconstrained functions may also be minimized, and the conjugate direction method of Fletcher and Reeves [Fletcher 64a] is used for this purpose. The user must supply a main program to call solver subroutine along with an external subroutine to evaluate the objective function, constraint functions and the analytic gradient of the objective and currently active or violated constraint functions. At any given time in the minimization process, gradient information is required only for constraints which are active or violated. In this case, active or violated constraints are those that their values exceed from the initial fixed values for bound constraints [Vanderplaats 84]. Gradients are calculated by finite difference if this information is not directly obtainable, and a subroutine is included with solver for this purpose. Therefore, the MFD optimization procedure uses from several FORTRAN, C and ANSYS script shells. The concept of MFD is to find a feasible direction for descent. The basic steps in this method involve solving a linear or nonlinear programming subproblem to find the direction vector and then finding the step-length along this direction by performing a constrained one-dimensional search. After updating the current point, the above steps are repeated until the termination criterion is satisfied. The main optimization program uses from one subprogram. The objective function calculation starts from the inside of main program using an interface, i.e., call_program.c that sends the input data to ANSYS solver. The modeling of structure, defining of its boundary conditions, and external excitations performed in an ANSYS file, i.e., ansysinp.dat. The finite element analysis carried out by ANSYS using this ansysinp.dat. A script shell can compile the FORTRAN and C programs and links them to each other to build an executive file. Then this executive file is ready for sending to a high performance computer for the finite element analysis by the ANSYS solver. Having objective function calculated, then the required data for the continuation of optimization process transfer automatically to the main FORTRAN program. If the termination criteria are satisfied, then the main program terminates the optimization process and writes the results in an output file. If the termination criteria are not satisfied, then the new start design variables are being read from a file, i.e., data20000.input, and the optimization will be repeated.

The general algorithm of MFD can be described as follows:

Algorithm A.2 *MFD*

1. $K = 0$.
2. Set $\boldsymbol{\vartheta}^K$ and $\mathcal{F}^K$.
3. $K = K + 1$
4. Set $\boldsymbol{\vartheta}^K$ and $\mathcal{F}^K$.
5. If $K = 1$ then $h^K = -g(\boldsymbol{\vartheta}^{k-1})$.
6. If $K > 1$ then $h^K = -g(\boldsymbol{\vartheta}^{k-1}) + \frac{|g(\boldsymbol{\vartheta}^{K-1})|^2}{|g(\boldsymbol{\vartheta}^{K-2})|^2} h^{K-1}$.
7. $\alpha^K = -0.1|g(\boldsymbol{\vartheta}^K)|$.
8. $\vartheta^{K+1} = \vartheta^K + \alpha^K h^K$.
9. Calculate F^{K+1}.
10. Check stopping criterion.
11. Go to 3.

A.3 Program for Sequential Quadratic Programming

SQP solver is a Fortran package designed to solve the nonlinear programming problem: the minimization of a smooth nonlinear function subject to a set of constraints on the variables [Spellucci 99]. Since the algorithm makes no use of sparse matrix techniques, its proper use will be limited to small and medium sized problems with dimensions up to 300 (for the number of unknowns). The number of inequality constraints however may be much larger.

The SQP optimization procedure uses also from several FORTRAN, C and ANSYS script shells. The main optimization program uses from some subprograms. The objective function calculation starts from the inside of main program using an interface, i.e., call_program.c that sends the input data to ANSYS solver. The modeling of structure, defining of its boundary conditions, and external excitations performed in an ANSYS file, i.e., ansysinp.dat. The finite element analysis carried out by ANSYS using this ansysinp.dat. A script shell can compile the FORTRAN and C programs and links them to each other to build an executive file. Then this executive file is ready for sending to a high performance computer for the finite element analysis by the ANSYS solver. Having objective function calculated, then the required data for the continuation of optimization process transfer automatically to the main FORTRAN program. If the termination criteria are satisfied, then the main program terminates the optimization process and writes the results in an output file. If the termination criteria are not satisfied, then the new start design variables are being read from a file, i.e., data20000.input, and the optimization will be repeated.

The sequential quadratic programming is a generalization of Newton's method for unconstrained optimization. This method is considered to be an excellent method by many theoreticians. the general flowchart of this work is:

Algorithm A.3 *SQP*

1. $K = 0.$
2. Set $\vartheta_i^K,\ \mathcal{F}(\vartheta_i^K),\ g(\vartheta_i^K),\ H(\vartheta_i^K).$
3. $m^K(\boldsymbol{\vartheta}) = \mathcal{F}(\vartheta^K)+(\boldsymbol{\vartheta}-\vartheta^K)g_K^T+\frac{1}{2}(\boldsymbol{\vartheta}-\vartheta^K)^T H^K(\boldsymbol{\vartheta}-\vartheta_K)$
4. Find the ϑ_{*i}^K which minimizes m^K by MFD method.
5. $d_i^K = \vartheta_{*i}^K - \vartheta_i^K.$
6. Compute a step length λ^K.
7. $\vartheta_i^{K+1} = \vartheta_i^K + \lambda^K d_i^K.$
8. Check stopping criterion.
9. Update the hessian H^K.
10. $K = K + 1$, go to 2.

The user has to define the problem through function evaluation routines. This may be done in two ways: Method one gives any function and gradient evaluation code individually. In this case the parameter BLOC has to be set to FALSE. This is the default. Alternatively the user might prefer or may be forced to evaluate the problem functions by a black-box external routine. SQP code has a built-in feature for doing gradients numerically. This can be used for both methods of problem description. This is controlled by the variables ANALYT, EPSFCN, TAUBND and DIFFTYPE. If ANALYT=.TRUE. then the code uses the values from the EGRAD. routines or from FUGRAD, according to the setting of BLOC. If ANALYT=.FALSE., then numerical differentiation is done internally using a method depending on DIFFTYPE.

The user must supply an initial estimate of the solution of the problem, subroutines that evaluate objective function, constraints and their first partial derivatives. The user may use finite differences to achieve this and may tell this to the code via a parameter epsdif, the discretization step size and by setting analyt to false.

If the problem is large and sparse, the package should not be used, since SQP solver treats all matrices as dense. This program is based on a sequential quadratic programming method incorporating the exact $l_1 - merit$ function and a special BFGS quasi-Newton approximation to the Hessian. As long as the gradients of the equality constraints and of the inequalities which are near their boundaries are linearly independent, the method uses an equality constrained subproblem only which makes it especially fast. If there are no nonlinear constraints, the gradients of the bound and linear constraints are never recomputed, and it will work as a specialized algorithm for linearly constrained optimization, allowing infeasible iterates. All problem functions are evaluated only at points that are feasible with respect to the bounds. There is also an exhaustive programm explanation in between the computer codes of this method which guides the user through the optimization process.

A.4 Program for L-BFGS-B method

The purpose of algorithm L-BFGS-B is to minimize a nonlinear function of variables subject to the simple bounds, e.g., lower and upper bounds on the design variables. The user must supply the gradient, but knowledge about the Hessian matrix of objective function is not required. For this reason the algorithm can be useful for solving large problems in which the Hessian matrix is difficult to compute or is dense. The general flowchart of this method is:

Algorithm A.4 *L-BFGS-B*

1. $K = 0$.
2. Set $\vartheta_i^K,\ \mathcal{F}(\vartheta_i^K),\ g(\vartheta_i^K),\ B(\vartheta_i^K)$.
3. $m^K(\boldsymbol{\vartheta}) = \mathcal{F}(\vartheta^K) + (\boldsymbol{\vartheta} - \vartheta^K) g_K^T + \frac{1}{2}(\boldsymbol{\vartheta} - \vartheta^K)^T B^K (\boldsymbol{\vartheta} - \vartheta_K)$
4. Find $\boldsymbol{\vartheta}_*^K$ which minimize m^K subject to bounds.
5. $d_i^K = \vartheta_{*i}^K - \vartheta_i^K$.
6. Compute a step length λ^K.
7. Set $\vartheta_i^{K+1} = \vartheta_i^K + \lambda^K d_i^K$.
8. Check stopping criterion.
9. Update the BFGS approximation of hessian B^K.
10. $K = K + 1$, go to 2.

At each iteration (K), a limited memory BFGS approximation to the Hessian (B) is updated [Byrd 93]. This limited memory matrix is used to define a quadratic model of the objective function. A search direction is then computed using a two-stage approach: first, the gradient projection method and it is used to identify a set of active variables, i.e. variables that will be held at their bounds; then the quadratic model is approximately minimized with respect to the free variables. The search direction is defined to be the vector leading from the current iterate to this approximate minimizer. Finally a line search is performed along the search direction using the subroutine described in [More 90]. A novel feature of the algorithm is that the limited memory BFGS matrices are represented in a compact form that is efficient for bound constrained problems.

The user can control the amount of storage required by L-BFGS-B by selecting a parameter that determines the number of BFGS corrections saved. If no bounds are active at the solution, it is appropriate to stop the iteration when the norm of the gradient is sufficiently small. The corresponding quantity for the case when some bounds are active is the norm of the projected gradient.

The L-BFGS-B has several advantages as well as this code is easy to use, and the user need not supply information about the Hessian matrix or about the structure of the objective function, also the cost of the iteration is low, and is independent of the properties of the objective function. Therefore L-BFGS-B is recommended for solving large problems in which the Hessian matrix is not sparse or is difficult to compute. However L-BFGS-B suffers from the some drawbacks as well as it is not rapidly convergent, and on difficult problems can take a large number of function evaluations to converge, on highly ill-conditioned problems the algorithm may fail to obtain high accuracy in the solution, and the algorithm cannot make use of knowledge about the structure of the problem to accelerate convergence.

The L-BFGS-B optimization procedure includes of several FORTRAN, C and ANSYS script shells. The main optimization program is LBFGS-DRIVER2.F90 and it uses from one subprogram, i.e., LBFGS-B.F90. The objective function calculation starts from the inside of LBFGS-DRIVER2.F90 using an interface, i.e., call_program.c that sends the input data to ANSYS solver. The modeling of structure, defining of its boundary conditions, and external excitations performed in an ANSYS file, i.e., ansysinp.dat. The finite element analysis carried out by ANSYS using this ansysinp.dat. A script shell can compile the FORTRAN and C programs and links them to each other to build an executive file. Then this executive file is ready for sending to a high performance computer for the finite element analysis by the ANSYS solver. Having objective function calculated, then the required data for the continuation of optimization process transfer automatically to the main FORTRAN program. If the termination criteria are satisfied, then the main program terminates the optimization process and writes the results in an output file. If the termination criteria are not satisfied, then the new start design variables are being read from a file, i.e., data20000.input, and the optimization will be repeated.

A.5 Program for Controlled Random Search Method

Controlled random search method is a procedure for constructing a sequence $\left\{\vartheta^K\right\}$ of points that converges to a point at which the global minimizer for $\mathcal{F}$ is attained or approximated. A random search routine UNIRANDI([Jarvi 73]), is used in this case.

The CRSM optimization procedure uses also from several FORTRAN, C and ANSYS script shells. The main optimization program uses from one subprogram. The objective function calculation starts from the inside of main program using an interface, i.e., call_program.c that sends the input data to ANSYS solver. The modeling of structure, defining of its boundary conditions, and external excitations performed in an ANSYS file, i.e., ansysinp.dat. The finite element analysis carried out by ANSYS using this ansysinp.dat. A script shell can compile the FORTRAN and C programs and links them to each other to build an executive file. Then this executive file is ready for sending to a high performance computer for the finite element analysis by the ANSYS solver. Furthermore, the main routine gives a computational evidence, that the best local minimum found is with high probability the global minimum. This routine calls a local search routine, and a routine for generating random numbers. The subroutines are written in FORTRAN. The user has to provide a main program doing the input-output, and a subroutine capable of computing the objective function value for any point in the parameter space.

The general algorithm of this method is:

Algorithm A.5 *CRSM*

1. K=0.
2. Set K = 1, choose a probability distribution P^l on $\boldsymbol{\vartheta}_K$.
3. Sample the probability distribution P^l to obtain the set of l design points $\boldsymbol{\vartheta}^l_K$.
4. At each of these points, calculate F^l_K.
5. Find the optimum F^l_K and put it to a saving list.
6. Using a fixed and algorithm-dependent rule, construct the probability distribution P_{k+1} on $\boldsymbol{\vartheta}$
7. Checking stopping criterion.
8. $K = K + 1$ and go to 3.

Having objective function calculated, then the required data for the continuation of optimization process transfer automatically to the main FORTRAN program. If the termination criteria are satisfied, then the main program terminates the optimization process and writes the results in an output file. If the termination criteria are not satisfied, then the new start design variables are being read from a file, i.e., data20000.input, and the optimization will be repeated.

A.6 Program for Simulated Annealing Method

SA solver tries to find the global optimum of an N dimensional function. It moves both up and downhill and as the optimization process proceeds, it focuses on the most promising area. This method chooses randomly a trial point within the step length (for a design vector of length n) of the user selected starting point. The function is evaluated at this trial point and its value is compared to its value at the initial point.

In a maximization problem, all uphill moves are accepted and the algorithm continues from that trial point. Downhill moves may be accepted; the decision is made by the Metropolis criteria. It uses T (temperature) and the size of the downhill move in a probabilistic manner. The smaller T and the size of the downhill move are, the more likely that move will be accepted. If the trial is accepted, the algorithm moves on from that point. If it is rejected, another point is chosen instead for a trial evaluation. The general flowchart of this method is:

Algorithm A.6 *SA*

1. K=0.
2. Set ϑ_i^K, Step vector v_i^K, Temperature T^K, Reduction coefficient r_T.
3. Compute $\mathcal{F}^K$.
4. Generate a new random design based on current T^K.
5. Is new design better?, then go to 6. If not, go to 7.
6. Replace current solution with new solution.
7. Reached max tries for this temperature?, If yes, then go to 4. If not, go to 8.
8. Decrease temperature by specified rate.
9. Lower temperature bound reached?, If no, then go to 4. If yes, stop.

Each element of step length periodically adjusted so that half of all function evaluations in that direction are accepted. A fall in T is imposed upon the system with the RT variable by T(K+1) = RT*T(K) where K is the Kth iteration. Thus, as T declines, downhill moves are less likely to be accepted and the percentage of rejections rise. Thus, as T declines, the step length falls and SA focuses upon the most promising area for optimization. Indeed a minimization problem can simply build by multiplying the objective function of a maximization problem in -1.

The parameter T is crucial in using SA successfully. It influences the step length, the step length over which the algorithm searches for optima. For a small initial T, the step length may be too small; thus not enough of the function might be evaluated to find the global optima. To determine the starting temperature that is consistent with optimizing a function, it is worthwhile to run a trial run first (Set RT=1.5 and T=1.0). With RT>1.0, the temperature increases and the step length rises as well. Finally it is recommendable to select the T that produces a large enough step length.

The SA optimization procedure uses from one FORTRAN, one C and one ANSYS script shell. The main optimization program is SA.F90. The objective function calculation starts from the inside of SA.F90 using an interface, i.e., call_program.c that sends the input data to ANSYS solver.

The modeling of structure, defining of its boundary conditions, and external excitations performed in an ANSYS file, i.e., ansysinp.dat. The finite element analysis carried out by ANSYS using this ansysinp.dat. A script shell can compile the FORTRAN and C programs and links them to each other to build an executive file. Then this executive file is ready for sending to a high performance computer for the finite element analysis by the ANSYS solver.

Furthermore, the main routine gives a computational evidence, that the best local minimum found is with high probability the global minimum. This routine calls a local search routine, and a routine for generating random numbers. The subroutines are written in FORTRAN. The user has to provide a main program doing the input-output, and a subroutine capable of computing the objective function value for any point in the parameter space.

A.7 Program for Genetic Algorithm Method

GA solver is a fully self-contained, general purpose optimization subroutine. The general algorithm of this method is:

Algorithm A.7 *GA*

1. Set $K = K + 1$.
2. Set a population of l chromosomes ($\boldsymbol{\vartheta}^l$).
3. Evaluate the objective function values of l chromosomes ($\mathcal{F}^l$).
4. Create new chromosomes by applying fitness scaling to the chromosomes, and recombining fit parent encodings.
5. Delete members of the population to make room for the new ones.
6. Evaluate each new chromosome as in step 3, and insert it into the population.
7. If the stopping criterion has been satisfied, stop and return the chromosome with best fitness, otherwise continue with step 4.

The GA [Charbonneau 03] optimization procedure uses also from several FORTRAN, C and ANSYS script shells. The main optimization program uses from one subprogram. The objective function calculation starts from the inside of main program using an interface, i.e., call_program.c that sends the input data to ANSYS solver. The modeling of structure, defining of its boundary conditions, and external excitations performed in an ANSYS file, i.e., ansysinp.dat. The finite element analysis carried out by ANSYS using this ansysinp.dat. A script shell can compile the FORTRAN and C programs and links them to each other to build an executive file. Then this executive file is ready for sending to a high performance computer for the finite element analysis by the ANSYS solver.

In this thesis, the number of individuals in a population is 100, the number of generations over which solution is to evolve is 500, the crossover probability is 0.85 (must be <=1.0), the mutation mode is variable, the initial mutation rate is 0.005 (the mutation rate is the probability that any one gene locus will mutate in any one generation and it should be small), the minimum mutation rate is 0.0005 (must be >=0.0), the maximum mutation rate is 0.25 (must be <=1.0), and the reproduction plan is Steady-state-replace-worst.

A.8 Program for Hybrid Design of Experiments

The general algorithm of HDOE can be described as follows:

Algorithm A.8 *HDOE*

1. K=0.
2. Set $\boldsymbol{\vartheta}_m^K$, $m = 1, 2, \cdots, n$ and $\mathcal{F}_m^K$.
3. Generate an approximate objective function based on $\boldsymbol{\vartheta}_m^K$ (linear, quadratics, etc.).
4. Find the minimum of approximate objective function by Simplex method.
5. Check stopping criterion.
6. $K = K + 1$, go to 2.

The HDOE solver has two parts consisting of objective function approximating and optimizing. The function approximation part which includes some routines to make a polynomial approximation for the real objective function. The HDOE optimization procedure uses from several FORTRAN, C and ANSYS script shells. The main optimization program is uses from some subprogram. The main program begins the optimization process using an interface, i.e., call_program.c that sends the input data to ANSYS solver. The modeling of structure, defining of its boundary conditions, and external excitations performed in an ANSYS file, i.e., ansysinp.dat. The finite element analysis carried out by ANSYS using this ansysinp.dat. A script shell can compile the FORTRAN and C programs and links them to each other to build an executive file. Then this executive file is ready for sending to a high performance computer for the finite element analysis by the ANSYS solver.

In this dissertation, a linear approximation approach is considered which needs n+1 design points from an objective function with n design variables. The approximation codes were taken from the well-known book of "Numerical Recipes" [Press 02] using xlift.f90 routines. The user must set NPT= n+1 in this routine for the linear function approximation. Then n+1 design points will be calculated using ANSYS solver and the approximation solver builds a linear approximation for the real objective function. Now the Simplex method is being used to calculate the minimum of this approximated function. The user must also set the upper and the lower bound constraints in the main program. The initial design required by the xamoeba.f90 routine for the Simplex optimization method can be produced by an uniform random number generator inside the design space. The final optimization outputs are available in DOEOUT.dat. The user should not alter any other parameters inside the codes when the selected approach is linear function approximation. Having objective function calculated, then the required data for the continuation of optimization process transfer automatically to the main FORTRAN program. If the termination criteria are satisfied, then the main program terminates the optimization process and writes the results in an output file. If the termination criteria are not satisfied, then the new start design variables are being read from a file, i.e., data20000.input, and the optimization will be repeated.

A.9 Program for Hybrid Neural Networks

The general algorithm of this method is:

Algorithm A.9 *HNN*

1. Produce $\boldsymbol{\vartheta}_m^K,\ m =\ 1,\ 2, \cdots,\ n$ and $\mathcal{F}_m^K$.
2. Train the neural network based on the initial designs.
3. Use the trained neural network as the objective function.
4. Find the optimum of new objective function by method of simulated annealing.
5. Check stopping criterion.
6. Go to 4.

The HNN optimization routine uses from the FORTRAN, C and ANSYS script shells. The objective function calculation starts from the inside of main optimization program using an interface, i.e., call_program.c that sends the input data to ANSYS solver. The modeling of structure, defining of its boundary conditions, and external excitations performed in an ANSYS file, i.e., ansysinp.dat. The finite element analysis carried out by ANSYS using this ansysinp.dat. A script shell can compile the FORTRAN and C programs and links them to each other to build an executive file. Then this executive file is ready for sending to a high performance computer for the finite element analysis by the ANSYS solver. Having objective function calculated, then the required data for the continuation of optimization process transfer automatically to the main FORTRAN program. If the termination criteria are satisfied, then the main program terminates the optimization process and writes the results in an output file. If the termination criteria are not satisfied, then the new start design variables are being read from a file, i.e., data20000.input, and the optimization will be repeated.

The NN solver has also two specific parts as a function approximation part and a function optimization part. The function approximation part calculates at first the specified number of design points by the user to train a virtual objective function based on these points using the neural networks method. It is up to user to define how many points should be initially calculated by the ANSYS solver at this regard. In this dissertation, 110 real design points, i.e. 110 real objective function values, are calculated by ANSYS solver. The main specific parameters in the NN routine and their values in this dissertation are the number of epochs (EPOCHES=100), number of hidden neurons (NHIDDEN=5), learning rate for input-hidden weights (ALR=0.1), learning rate for hidden-output weights (BLR=0.01). Now a virtual objective function is produced by NN solver and it will be optimized by the SA method. The required parameters for SA solver remains unchanged and are similar with the case when the SA solver works as usual to find the minimum of an objective function. Just the user must provide an initial start design for SA solver and the maximum allowable number of objective function evaluations.

A.10 Program for Tabu Search Method

The TS optimization routine uses from several CPP and ANSYS script shells. The main optimization program uses from several subprograms. The objective function calculation starts from the inside of main program and it sends the input data to ANSYS solver. The modeling of structure, defining of its boundary conditions, and external excitations performed in an ANSYS file, i.e., ansysinp.dat. The finite element analysis carried out by ANSYS using this ansysinp.dat. A script shell can compile the CPP programs and links them to each other to build an executive file. Then this executive file is ready for sending to a high performance computer for the finite element analysis by the ANSYS solver.

The user must provide the set of initial designs, and some control parameters as well as the number of design variables, the dimension of tabu list (TabuListDim=5) and the maximum number of iterations (ItMaxNb). The other required parameters are being set with respect to the dimension of objective function, automatically. Having objective function calculated, then the required data for the continuation of optimization process transfer automatically to the main FORTRAN program. If the termination criteria are satisfied, then the main program terminates the optimization process and writes the results in an output file. If the termination criteria are not satisfied, then the new start design variables are being read from a file, i.e., data20000.input, and the optimization will be repeated.

The general algorithm of this method is:

Algorithm A.10 *TS*

1. Set the initial designs.
2. Set the dimension of tabu list.
3. Perform the diversification and locate the most promising areas.
4. Perform intensification within one promising area of the solution space to find the optimum design.
5. Check stopping criterion.
6. Go to 3.

A.11 Program for Mid-range Multi-points Method

The MMP optimization procedure uses also from several FORTRAN, C and ANSYS script shells. The main optimization program uses from some subprogram. The objective function calculation starts from inside main program by a subroutine using an interface, i.e., call_program.c that sends the input data to ANSYS solver. The modeling of structure, defining of its boundary conditions, and external excitations performed in an ANSYS file, i.e., ansysinp.dat. The finite element analysis carried out by ANSYS using this ansysinp.dat. A script shell can compile the FORTRAN and C programs and links them to each other to build an executive file. Then this executive file is ready for sending to a high performance computer for the finite element analysis by the ANSYS solver. Having objective function calculated, then the required data for the continuation of optimization process transfer automatically to the main FORTRAN program. If the termination criteria are satisfied, then the main program terminates the optimization process and writes the results in an output file. If the termination criteria are not satisfied, then the new start design variables are being read from a file, i.e., data20000.input, and the optimization will be repeated.

For the approximation part of MMP code, depending on the search direction, the value of parameter V can be either +1 or -1 when the search direction is positive or negative respectively. Default value for small reduction in moving limit is PHI3=0.7 and and default value for large reduction in moving limit is PHI2=0.3. Also, Cmax=0.01, is the default value for allowable constraint violations and N is the number of design variables.

The general algorithm of this method is:

Algorithm A.11 *MMP*

1. $K = 0$.
2. $K = K + 1$
3. Select a model of objective function approximation.
4. Select the set of design points ($\boldsymbol{\vartheta}$) to be used in the fitting of the model.
5. Calculate the unknown function parameters and build the approximative function.
6. Find the optimum of approximated function.
7. Set the move limit using the newly found optimum.
8. Generate one or more new design points within the move limits to base the new approximations on and use data from previous steps.
9. Check stopping criterion.
10. Go to 2.

A.12 Program for Newton Method

NewtonŠs method is a very popular method which is based on TaylorŠs series expansion.

The NM optimization procedure uses also from one FORTRAN, one C and one ANSYS script shells. The objective function calculation starts from the inside of main optimization program using an interface, i.e., call_program.c that sends the input data to ANSYS solver. The modeling of structure, defining of its boundary conditions, and external excitations performed in an ANSYS file, i.e., ansysinp.dat. The finite element analysis carried out by ANSYS using this ansysinp.dat. A script shell can compile the FORTRAN and C programs and links them to each other to build an executive file. Then this executive file is ready for sending to a high performance computer for the finite element analysis by the ANSYS solver. Having objective function calculated, then the required data for the continuation of optimization process transfer automatically to the main FORTRAN program. If the termination criteria are satisfied, then the main program terminates the optimization process and writes the results in an output file. If the termination criteria are not satisfied, then the new start design variables are being read from a file, i.e., data20000.input, and the optimization will be repeated. The general algorithm of this method is:

Algorithm A.12 *NM*

1. $K = 0$.
2. Set $\boldsymbol{\vartheta}^K,\ \mathcal{F}^K(\boldsymbol{\vartheta}),\ g^K(\boldsymbol{\vartheta}),\ H^K(\boldsymbol{\vartheta})$.
3. $\boldsymbol{\vartheta}^{K+1} = \boldsymbol{\vartheta}^K - (H^K)^{-1} g^K$.
4. Calculate $\mathcal{F}^{K+1}$.
5. Check stopping criterion.
6. $K = K + 1$, go to 2.

The NM program performs the task to solve unconstrained minimization problems using a modified version of Newton's method. However, simple bound constraints are imposed for solving of such optimization problems. R1 and R2 are Hessian modification parameters and can be selected for a range of (0.0000001 to 0.001) and (0.001 to 10), respectively. In this dissertation the values of R1 and R2 are considered as 0.001 and 5. GAMMA is a parameter used in line search when Hessian is modified. The recommended value for GAMMA is 2 to 10. In this dissertation, a value of 10 is considered for GAMMA. A large value of GAMMA results in a line search over a wider rang. BETA is a parameter used in step-size rule; if the current step does not give a reduction in function value, the step-size is cut down by a factor BETA. The recommended value for BETA is 0.1 to 0.4. In this dissertation a value of 0.4 for BETA is used. LIMIT is the maximum number of total iterations. Note that the recommended ranges for parameters values are not foolproof. Experimentation with other values may be required in unusual cases.

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Die vorliegende Arbeit wurde am Institut für Festköpermechanik der Technischen Universität Dresden angefertigt. Die wissenschaftliche Betreuung erfolgte durch Herrn Prof. Dr.-Ing. Prof. h.c. Hans-Jürgen Hardtke und durch Herrn Prof. Dr.-Ing. Steffen Marburg seitens der Fachrichtung Maschinenwessen der Technischen Universität Dresden.

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